Smartphone Locations Reveal Patterns of Cooling Center Use During Extreme Heat in Los Angeles County

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For More Information

For more information on cooling center resources in Los Angeles County, please visit https://ready.lacounty.gov/heat/.

To see the story map of our project, please visit https://tinyurl.com/LAHeatwaves.

Table of Contents

Executive Summary

Projections of the future climate of the Los Angeles area show an unequivocal increase in extreme heat. As the climate warms, the temperature in developed regions is compounded by the urban heat island effect. As a result, Los Angeles residents are especially vulnerable to extreme heat events, or heatwaves. Fortunately, Los Angeles has cooling centers or sites that attempt to mitigate the harmful effects of extreme heat by providing proper air conditioning and relief from the sun. Formal cooling centers are facilities that are freely open to the public for relief from the heat, such as libraries and recreation centers. Informal cooling centers are open buildings or businesses that provide relief from the heat in addition to their primary function, such as shopping centers, movie theaters, and restaurants.

Our project assesses cooling centers within the county to identify patterns of use. We piloted a novel method of analyzing the use of both formal and informal cooling centers using mobile device (smartphone) location data, otherwise referred to as “mobility data.” This study uses a mobility dataset that covers a two-month summer period in 2017 in Los Angeles County (LA County). The results are then used to suggest climate-resilient policies to the County of Los Angeles Department of Public Health and the Chief Sustainability Office and identify suitable locations for future heat infrastructure projects that will help protect vulnerable communities. The study is partitioned into three research questions addressing the themes of occupancy, vulnerability, and transportation.

Cooling centers in this study were classified as formal county, formal non-county, or informal cooling centers. Formal cooling centers are parks, libraries, and senior and community centers operated by county or non-county government agencies. Informal cooling centers include pools, shopping centers, and recreation centers that LA County residents often visit to cool down. Layers of the cooling center types were developed on ArcGIS with publicly available datasets. To analyze occupancy during hot days, six pairs of hot (maximum temperatures greater than 94.0 °F) and baseline days were selected during July and August 2017 based on historical weather data. Mobility data were acquired from Outlogic, a private location data provider that collects data on consenting users of third-party mobile phone applications that track spatial data. These data were subset by each hour between 12:00 pm and 4:00 pm for the sample days, with inaccurate data points omitted, to count “pings” (unique device locations) that intersected with the cooling center building footprints.

We first examined cooling center occupancy comparing occupancy by cooling center types, and occupancy comparisons between hot and baseline days. Occupancy was measured by the number of pings in a cooling center during a given hour and standardized for variations in cooling center type area and total pings on the sample day. An additional extrapolation of this proportion to the 2017 LA County population yielded occupancy units of people per acre. A ratio of unique pings in a given center type to total pings was calculated on hot and baseline days to further assess duration, where a lower ratio suggested longer cooling center occupancy. For pairs of hot and baseline days, occupancy counts were assessed for significant differences.

We then assessed the vulnerability of cooling center users. To do this, the user's nighttime resting location, defined as mobile phone ping locations from 1:00 am to 5:00 am, was collected and intersected with the “Social Sensitivity Index” layer used and provided by LA County. This index was divided to categorize county tracts into low, moderate, or high sensitivity. The cooling

center locations were also intersected with this layer to assess if occupancy is correlated with the vulnerability of a community. Phone interviews with employees of cooling centers in the San Fernando Valley region were completed to provide qualitative analysis of heat event procedures and to help explain the quantitative occupancy results.

Finally, we focused on cooling center accessibility by public transportation and walking. The coordinates of public transportation (bus, rail, and subway) stops in LA County were collected from publicly available data and compared with cooling center locations using GIS to determine Euclidean distance between cooling centers and the nearest bus stop. To assess the walkable potential of cooling centers, the Euclidean distance was calculated between nighttime resting locations of cooling center users, as identified with mobility data, and the cooling center that each individual utilized. As users of cooling centers were already identified for the vulnerability analysis, this spatial analysis could reveal more trends of our existing sample of users for developing policy.

Results of the occupancy analysis showed that hot days had a lower occupancy ratio overall than baseline days, and occupancy was relatively constant for hot days while generally decreased during baseline days. These results are consistent with the generalized behavior of users staying in cooling centers during peak heat hours of hot days to escape the heat. Formal non-county centers were found to be the most used center types, followed by informal cooling centers and formal county centers. Occupancy during hot and baseline days did not exhibit a pattern that was consistent across all center types, although use was comparatively higher at formal County cooling centers during extreme heat days compared to baseline days. Findings in occupancy duration indicate the potential for utilizing smartphone mobility data to assess and inform public policy regarding cooling centers as heat mitigation strategies.

The social vulnerability analysis showed that generally, cooling centers are evenly distributed across social sensitivity groups. However, formal centers tend to be located in areas of high vulnerability, while informal cooling centers are more evenly distributed between low, moderate, and high sensitivity areas. Usage on hot days compared to baseline in high vulnerability tracts demonstrates that: 1) centers in high vulnerability tracts serve more people carrying devices from high vulnerability tracts than people from low vulnerability tracts, and 2) individuals from high vulnerability tracts showed greater cooling center use on extreme heat days than those from low vulnerability tracts. The informational interviews revealed that limited avenues of information dissemination, especially in reaching the homeless and elderly, could cause cooling centers to be underutilized.

The transportation analysis revealed that as the distance to the nearest public transit stop increased, the number of visits decreased, during both hot and baseline days. For formal non-county centers, as social sensitivity of tracts increased from low to high, users tended to visit the centers that were closer to public transportation. The percentage of visits to cooling centers within walking distance from the users' resting locations decreased on hot days compared to baseline across all cooling center types, suggesting that people may potentially drive to further cooling centers on hot days or just stay at home.

We used our quantitative and qualitative results to craft policy recommendations for LA County. The main takeaways are to increase public communication about cooling centers, incorporate cooling centers in heat mitigation plans, and use public transportation access as a key factor in planning new centers. Due to the novel methods used in this project, there is limited literature to support our conclusions. The patterns of occupancy revealed in our analysis would be strengthened by increasing the sample days.

Chapter 1. Introduction

Since 1850, global surface temperature has increased at an unprecedented rate due to a rise in anthropogenic emissions of greenhouse gasses and their long-term accumulation in the atmosphere. Robust evidence shows that climate change has increased the frequency and intensity of region-specific extreme weather events, such as heavy precipitation, tropical cyclones, droughts, and heatwaves (IPCC, 2021). In Southern California—a region with a population of approximately twenty-five million people, ten million of whom live in the greater Los Angeles Area—the Intergovernmental Panel on Climate Change (IPCC) predicts an increase in heat extremes (extreme temperature days above 95°F) which poses a growing risk for the people of Southern California (IPCC, 2021; Hulley et al., 2020).

Southern California typically experiences hot, dry summers due to its Mediterranean climate. The complex topography and population density of Southern California result in non-uniform predictions in climate projections. Researchers have categorized the complexity into three distinct subregions: "rural," "inland urban," and "coastal urban." Inland urban areas are projected to experience the greatest rise in heatwave frequency, duration, intensity, and season length (Hulley et al., 2020). LA County is a highly developed, urban region that is prone to the urban heat island effect. Cities experience higher temperatures than undeveloped surrounding areas since buildings, roads and structures absorb and re-emit heat (US EPA, 2021). This effect is also caused by a lack of green space in cities, which can reflect sunlight, provide shade, and cool their surroundings through evapotranspiration of water.

Considering these three factors—a typically hot climate, an intensification of extreme heat events due to climate change, and the urban heat island effect—LA County must prepare its population for a hotter future. Excessive environmental heat load and exposure may lead to common heat illnesses such as heat stroke, heat exhaustion, and heat cramps (Casa et al., 2015; Kenny et al., 2010). Heat exposure may be exacerbated by social inequities and therefore pose a higher risk specifically to the elderly and those with pre-existing health conditions (Yang et al., 2021).

One adaptation to the increasing health risks posed by extreme heat events in urban environments is the implementation of cooling center infrastructure that allows individuals to maintain normal body temperatures. Within LA County, citizens have access to both formal and informal cooling centers. Formal cooling centers are specific public facilities that are free and open to the public for relief from the heat, such as libraries, community & senior centers, and county parks. Informal cooling centers are open buildings that provide relief from the heat in addition to their primary function, such as shopping centers, movie theaters, grocery stores, and restaurants. The availability and accessibility of these facilities are especially important for socioeconomically disadvantaged communities who may not have access to private cooling systems—like air conditioning systems or fans—and are thus the most at-risk of heat-related illnesses.

Because of LA County's vast size and population, multiple stakeholders are involved in the operation and management of cooling centers in the county, including the County Department of Public Health, County Chief Sustainability Office, and the County Office of Emergency Management (Chu et al., 2021). Los Angeles County's Cooling Center Program has created an interactive map of free and accessible county facilities for heat relief. The County of Los

Angeles Sustainability Plan outlines the need to develop practices and requirements of cooling center use under Strategy 1F, which focuses on strengthening community capacity to respond to emergencies. Establishing climate resilient plans and policies will be essential for our government to protect its citizens. These policies must be backed by current research.

Despite the perceived importance of cooling centers during extreme heat events, limited research has been completed to assess their use. The existing research focuses on evaluating the accessibility of cooling centers, rather than effectiveness (Widerynski et al., 2017). Fraser et al. (2018) examined and compared the distribution of public cooling center networks in Los Angeles County and Maricopa County, Arizona. They discovered that the spatial distribution of cooling centers tends to be clustered around places with existing cooling facilities instead of being closer to the more vulnerable groups and communities, preventing the use of cooling centers by people at high risk. Chu et al. (2021) evaluated current policies and measures adopted by the County of Los Angeles to address extreme heat challenges and conducted a literature review and a spatial analysis of the cooling centers in Los Angeles County. They discussed current issues associated with cooling centers, including under-use, high cost of operation, and health concerns related to the ongoing COVID-19 pandemic. Researchers mention that it is hard to evaluate cooling centers at a broad scale because of the randomness of each extreme heat event and affected community (Widerynski et al., 2017). Moreover, individual behaviors are hard to measure, understand, or predict, so does the way individuals act during extreme heat events or utilize public cooling resources (Fraser et al., 2018). Historically, researchers only had limited data from informant surveys to provide localized detail into the prevalence of certain behaviors.

We propose the adoption of mobile device location data, otherwise referred to as "mobility data," as a novel method of analyzing the use of formal and informal cooling centers. Observing human mobility has often elucidated patterns and led to larger conclusions about human behaviors, society, and the lived environment. Many third-party service providers have used this mobility data from mobile devices or similar location-acquisition technology to analyze consumer trends and inform the creation of personalized ads, as well as curate user profiles to "better monetize the collected data" (Boutet & Gambs, 2019). While use of these data has caused concern over user privacy, mobility data has also been an integral force in understanding human behavior and public health. Mobility data has aided tremendous advancements in visualizing the COVID-19 pandemic and bolstering our understanding of climate change impacts, ultimately allowing better predictions about future conditions—such as the increasing intensity of heat waves (Grantz et al., 2020; Hatchett et al., 2021; Yin et al., 2021). For these conditions, we know that threats such as heat exposure and heat vulnerability are measured to identify at-risk communities and determine the level of risk in the form of heat exposure indices (HEI) and heat vulnerability indices (HVI) (Yin et al., 2021). Mobility data can be used as a new research tool to expand upon and improve these models, as well as provide valuable insight into cooling center use, the demographics of cooling center users, and other areas lacking in research, such as transportation and accessibility to these cooling centers.

Our team tested the use of mobile phone location data to assess how people use formal and informal cooling centers during extreme heat events. These data were obtained as part of a related UCLA project and cover a two-month summer period in 2017 in LA County that had a high number of heat-related deaths. Our study is partitioned into three research questions addressing the themes of occupancy, vulnerability, and transportation.

Our three main themes are each addressed in the chapters that follow.

Chapter 2 addresses the limited research regarding cooling center use by identifying informal/formal cooling centers in LA County and investigating the changes in occupancy and duration of use between those center types. We then assess the difference in cooling center usage during extreme heat and baseline days.

Chapter 3 investigates the feasibility of extracting vulnerability characteristics of cooling center users as inferred from mobility patterns to identify what communities these centers are serving, and if they match assessments of social vulnerability to extreme heat.

Chapter 4 evaluates how transportation affects the accessibility of these cooling centers. These data will be essential in supporting climate-resilient policies that can protect vulnerable communities.

Chapter 5 summarizes the results of the study and includes policy recommendations motivated by our analysis. Eventually, the County of Los Angeles Department of Public Health and the Chief Sustainability Office will be able to expand this pilot project to include a larger dataset and identify suitable locations for future heat infrastructure projects.

Chapter 2. Cooling Center Occupancy and Use

While the knowledge of heat warnings is “nearly universal” across all cities, knowledge regarding actions to take during extreme heat events is lacking. As a result, large cities in the U.S. have implemented strategies that raise awareness and inform individuals of best health practices. In this chapter, we will use mobility data as a tool to examine the usage of cooling centers to determine its efficacy as a method of mitigating the adverse outcomes of extreme heat events.

To understand individuals’ behavior and investigate the effectiveness of municipal heat preparation programs, Sheridan (2007) conducted a telephone survey across four American cities on public perception and response to heat warnings. Less than half of the respondents reported modifying their behavior and less than 2% of respondents cited traveling to a cooler location. The most common behavioral adaptation was staying indoors. Additionally, the CDC’s top recommendation to cope with extreme heat is the use of an air-conditioner (CDC, 2016), making it a central behavior examined among the studies that exist. While Sheridan (2007) found that 90% of respondents own air-conditioning units and 93% of those respondents used them during heat events, similar to findings from Sampson et al. (2013), the cost is a significant barrier for many individuals in deciding whether to use air conditioning or not. Public infrastructure, including cooling centers, thus poses an opportunity to alleviate the barriers that may prevent the ubiquitous adoption of health-promoting behavior.

Cooling centers, defined as “a location, typically an air-conditioned or cooled building that has been designated as a site to provide respite and safety during extreme heat” are commonly used across the U.S. to protect the public from extreme heat, reduce heat exposure, and address heat-related health risks (Fraser et al., 2018; Widerynski et al., 2017, p. 4). However, the limited research and studies that exist evaluate the accessibility of cooling centers, not necessarily the use and effectiveness of cooling centers (Widerynski et al., 2017). One common assumption is that since cooling centers provide a cool environment, it is logical to consider them effective in reducing heat-related morbidity and mortality (Widerynski et al., 2017). It also may be difficult to evaluate cooling centers on a broad scale not only because of the randomness of each extreme heat event and its affected community, but also because of the nature of human behavior. That is, individual behaviors are hard to measure, understand, or predict, as does the way individuals act during extreme heat events or utilize public cooling resources (Fraser et al., 2018; Widerynski et al., 2017). While cooling centers may be assumed to reduce health risks and complications from exposure to extreme heat, questions remain as to whether this infrastructure is indeed being utilized by individuals for cooling purposes when faced with extreme heat.

Furthermore, what defines a cooling center is quite broad given its relatively broad function. As such, the current literature has made few distinctions between formal and informal cooling centers. Most authors refer to both formal cooling centers and other cool spaces as “cooling centers” or “public cooling centers” (Fraser et al., 2018; Widerynski et al., 2017). Such cooling centers include indoor air-conditioned spaces like libraries, schools, malls, movie theaters, and community centers, and outdoor cooling centers like pools, beaches, parks, and public water features. Many authors suggest that no single group or organization should be in charge of cooling centers in any particular community (Nayak et al., 2017; Widerynski et al., 2017). Instead, diverse stakeholders need to be engaged in the design, implementation, and operation of cooling centers such as city/county governmental agencies, the department of transportation, schools, local businesses, non-profits, and emergency management agencies (Nayak et al., 2017; Widerynski et al., 2017). Key elements to consider according to Berisha et al. (2017) include facility visibility, accessibility, services communication and staff knowledgeability. Moreover, local authorities associated with or operating the formal cooling centers tend to encourage the use of alternative cooling shelters (Fraser et al., 2018). Fostering collaboration and allowing input among all agencies and levels of government is an essential step in setting up cooling centers (Widerynski et al., 2017). It leaves consideration on whether there is a need to separate formal and informal cooling centers, and how cooling centers should best be managed by the variety of stakeholders involved.

LA County's Cooling Center Program has created an interactive map of free and accessible county facilities for heat relief ("formal" cooling centers like libraries, community & senior centers, and county parks). Additionally, the program suggests people visit "informal" cooling indoor spaces like grocery stores, movie theaters, and shopping malls during peak heat hours.Because of LA County's vast size and population, multiple stakeholders participate in the operation and management of cooling centers in the county, including the County Department of Public Health, County Chief Sustainability Office, and the County Office of Emergency Management (Chu et al., 2021). Yet, limited research has been done on the use and effectiveness of cooling centers in LA County.

Fraser et al. (2018) examined and compared the distribution of public cooling center networks in LA County and Maricopa County, Arizona. They discovered that the current spatial distribution of cooling centers tends to be clustered around places with existing cooling facilities instead of being closer to the more vulnerable groups and communities, limiting the use of cooling centers by people at elevated risk. Chu et al. (2021) evaluated current policies and measures adopted by the County of Los Angeles to address extreme heat challenges and conducted a literature review and a spatial analysis of the cooling centers in LA County. They discussed current issues associated with cooling centers, including under usage, excessive cost of operation, and health concerns related to the ongoing COVID-19 pandemic. Similar to Fraser et al., Chu et al. (2021) also identified the inequitable spatial distribution of cooling centers and coined the term "cooling center deserts," where "residents lack adequate access to Cooling Centers by transit modes", including "driving, public transit, and walking" (p. 24). They highlighted a general lack of accessible cooling centers via public transportation and walking, and a need for cooling center alternatives to protect the public from extreme heat events. Chu et al. (2021) recommended creating social programming and making cooling centers more appealing, especially for key groups. Therefore, there is a need to better understand current cooling center use, user characteristics, and factors that may impact cooling center usage in order to improve cooling center programs equitably.

In order to bridge this gap of knowledge regarding cooling center locations and areas of service, and classification (between informal/formal), our project will use mobility data–location data collected from mobile phones and similar technology.

Recently, the integration of mobile devices has been analyzed to better visualize the use of human mobility data in several case studies. Many studies reference Call Detail Records (CDRs) provide metadata of a particular phone number's utilization; this includes details like the location of the call, duration, and participating parties to assume relations between the user and the locations (Bartley, 2022). The Southern District of Ulsa, South Korea compared static census data to mobile phone-based floating population data that "reflects real-time population movement based on the constant grid-cell unit" (Woo et al., 2021). Mobility data has been especially useful throughout the COVID-19 pandemic in detailing the spread of the COVID-19 virus and analyzing niche community changes, such as park visitations (Holec et al., 2021; Rice & Pan., 2021). Mobility data has also revealed important social implications, detailing differences in stay-at-home mandate cooperation because of socio-economic status (Huang et al., 2021). In one study by Boston University, devices dubbed "Thermochron iButtons" measure surrounding air temperature to analyze the "variability of individually experienced temperatures (IETS) within a single urban neighborhood" (Kuras et al., 2015). It was found that there is great heterogeneity in individually experienced temperatures. While geographic, social, and cultural aspects were similar, heat exposure varied greatly between individuals considering their daily lives, as each person had a unique mobility pattern (Kuras et al., 2015).

Mobility data thus presents a new scale in which we determine heat exposure and vulnerability—one that narrows risk down to specific neighborhoods and further, individual people. For our project, mobility data will be especially useful in evaluating how many people are visiting cooling centers (occupancy) and how long they are staying (duration). Additionally, an analysis of our mobility data will provide further insight on cooling center usage depending on the type of the center itself and the between days of interest. Our exploration of and use of the novel technique of mobility data analysis will hopefully expand our knowledge of cooling centers and their influence on mitigating harmful effects of extreme heat events.

Throughout this section of our project, we will answer the following research questions:

- What is the feasibility of using mobile phone device location data to evaluate changes in occupancy and duration of occupancy of formal and informal cooling centers within the County of Los Angeles?
- How often are informal cooling centers used in comparison to formal cooling centers?
- Is there a difference between cooling center use on extreme heat days compared with baseline use?

Methods

The methodology to evaluate the use of cooling centers in Los Angeles County is outlined below. This consists of the creation of center footprints, selecting study days based on the temperature, and the various methods related to assessing the usage of these cooling centers.

Building Footprints

We first created a database of the locations ("point layer") and building footprints ("polygon layer") for the cooling centers of interest. We defined "formal" cooling centers as libraries, senior and community centers, and parks, based on the Ready LA County website. Formal cooling centers were further categorized by whether the county agency operates the center or not. Based on the Los Angeles Barometer Survey results (A. Frazzini, personal communication, January 5, 2022), residents often visit other places like pools, beaches, restaurants, malls, stores, homes of friends, and indoor recreation centers to cool down. We analyzed the following "informal" cooling centers: pools, shopping centers, and recreation centers, which have relatively large footprints and accessible location data for feasible geospatial analysis. These types create a hierarchy of cooling centers that are used in this study (Figure 1).

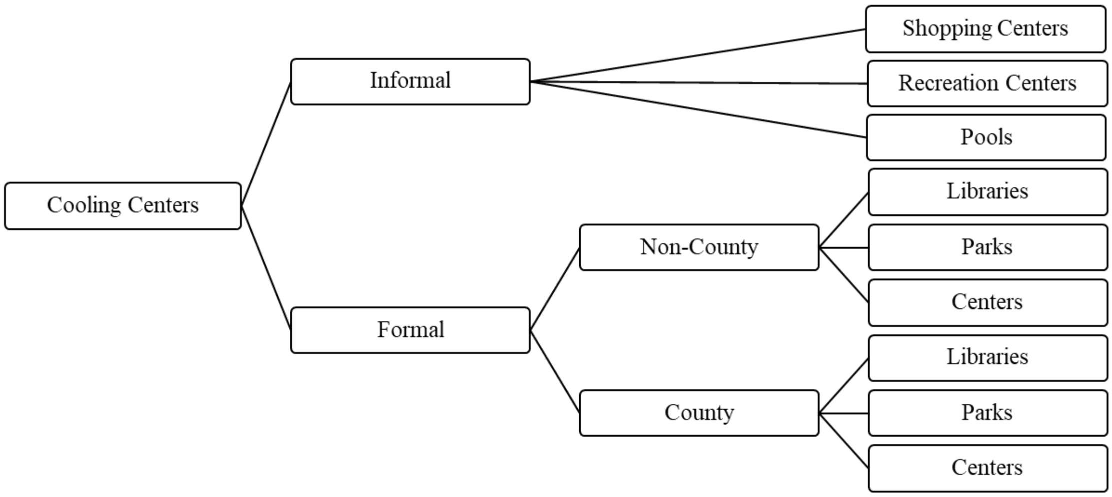


Figure 1. Summary of Cooling Center Categories

A point layer for 2021 formal county cooling centers was provided by the county. Because our analysis uses mobility data from July to August of 2017, the point layer was manually checked against the 2017 County Cooling Center List published by the LA County Department of Public Health to reflect the 2017 formal county cooling centers. Another point layer for formal county cooling centers was obtained from LA County ArcGIS Online Hub for confirmation of cooling center information and locations. Then, the formal county cooling centers were separated into the sub-categories of libraries, centers, and parks based on the most significant indoor air-conditioned facility at that location. However, the real-world distinctions between centers and parks are not always clear, as some community or senior center facilities are actually located within the parks, which complicated the categorization. In such cases, most facilities are labeled under the center category, resulting in the small number of formal county parks and building footprint areas covered. Therefore, it is also important to consider the usage and accessibility of parks and centers both individually and within the broader category of formal county cooling centers.

Point layers for formal non-county and informal cooling centers were obtained from the LA County ArcGIS Online Hub. The 2017 building footprint geodatabase was obtained from the Los Angeles Region Imagery Acquisition Consortium (LARIAC). After manually sorting through the point layer to remove irrelevant locations, the point layer was used to intersect with the LARIAC footprint layer to identify the cooling centers' footprints using GIS software (QGIS, ArcMap, or ArcGIS Pro). Because many point locations were not directly placed on a building and some cooling centers comprise more than one building, buffers were used to intersect the surrounding building footprints. Then, we manually checked each cooling center to identify the missing or incorrect building footprints, with reference to location information from the LA County Service Locator and satellite layers on Google Maps. This footprint matching step also confirmed if the cooling center was in place in 2017, given that most point layers were updated in 2021 or 2022.

The process of creating the polygon layers was primarily based on manual matching and checking, which was a time-consuming step and could be affected by human biases. To minimize potential human error, after creating a polygon layer for each center type, we cross-checked all the layers to remove duplicated centers or building footprints. More detail about the cooling center layer creation processes can be found in Appendix A.

A different workflow was employed for the formal non-county parks. We initially downloaded the park shapefile from the California Protected Areas Database (CPAD), which covers the entire area of the parks, including the open area. However, a critical criterion for a cooling center in our project is to be an air-conditioned building, so we filtered the park to only include those with multipurpose buildings, rooms, or centers that are publicly accessible. Similarly, for the formal county park layer, only such park facilities are included in the polygon layer. The non-county park shapefile was then used to intersect with the LARIAC layer to get the parks' facility footprints. Afterward, the formal non-county park polygon layer was used to match with the park point layer found on LA County ArcGIS Online Hub.

Temperature Data

To conduct a heat event analysis, we determined which days in our study period would correspond to a "heat day" and a "baseline day." Using data from a Los Angeles Times study (Phillips et al., 2021), we assessed the temperature records for each day of July and August of 2017. To focus on the hottest part of the day, we used the countywide average maximum temperature as our criteria for categorizing. In the two-month span, we found three two-day periods of heat days that contained six of the seven hottest days for July and August. For selection of comparison baseline days, we selected the day one week prior to each heat day. This allowed for a consistency of use by day of the week, and each pair of heat and baseline days had at least a nine-degree Fahrenheit difference in maximum temperatures. The hotter days of the pairs, which represent days with temperatures around or above the IPCC extreme heat threshold, were referred to as "hot days" to distinguish them from baseline days (Table 1).

Table 1. Summary of Hot and Comparison Baseline Days.

Hot Days		Baseline Days	
Day	**Max Temp (°F)**	**Day**	**Max Temp (°F)**
Saturday, 07/08/2017	96.5	Saturday, 07/01/2017	78.5
Sunday, 07/09/2017	98.7	Sunday, 07/02/2017	77.5
Wednesday, 08/02/2017	95.7	Wednesday, 07/26/2017	84.1
Thursday, 08/03/2017	94.3	Thursday, 07/27/2017	84.7
Wednesday, 08/30/2017	97.2	Wednesday, 08/23/2017	84.2
Thursday, 08/31/2017	95.9	Thursday, 08/24/2017	80.2

Mobility Data

Mobility data were acquired through Outlogic, a private provider of large location data. Each mobile phone device in the dataset attained a unique identifier, and the coordinates of these devices were randomly logged throughout various times of the dataset period. Outlogic assembled this dataset from acquired spatial data of mobile phones in LA County, in which consenting third-party applications tracked the spatial location of mobile phone devices, as agreed upon in the terms of use of the applications. Additional attributes that were captured in the data set included horizontal and vertical accuracy, heading, device model, speed of the device, and time of device location recorded in Unix time ("ping").

The mobility data were subset for July 2017 to August 2017 to cover the heatwave events identified from the weather data analysis. During the study period, the total number of pings for each hour ranged from 133,648 pings to 1,748,414 pings, indicating that the dataset represented between 1.02% to 17.17% of the true population of Los Angeles County in 2017. Data were analyzed in aggregate to maintain the anonymity of the individuals that corresponded to the mobile phone devices.

Occupancy Counts

The main component of our project, therefore, required that we subset our large mobility data files (60 GB) for relevant device IDs, with relevant IDs determined as location data with the following characteristics:

- Ping within any of our identified center types
- Ping within the timeframe of 12:00 pm to 4:00 pm on each given day
- Ping with a speed attribute < 3 meters/second
- And ping with a location accuracy of at least 25 meters horizontally

Using Python language, we created a notebook in Google Colab that filtered each day's dataset to our specifications (Appendix D). In particular, it was important that we only assessed the data from mobile IDs that were walking speed or less (< 3 meters/second) and of reasonable horizontal accuracy (at most 25 meters) to ensure that any pings from passing vehicles would not be captured. We determined these cutoff criteria by using a combination of historic literature for walking speed and analyzing the distribution of horizontal accuracy in our dataset (Peng et al., 2020). For horizontal accuracy, the majority of the data fell within an accuracy of 25 meters, with only a few outlier mobile devices sending low-accuracy location data. A threshold of 25 meters has been used in other studies (Rambhatla et al., 2022).

After creating a new data frame with the relevant mobile IDs, we created a Python class to identify (1) which mobile IDs were in a cooling center, and (2) which cooling center location they were in. Matching the mobile IDs to the shapefile polygons utilized the longitude and latitude attribute which was combined into one coordinate per ping in Colab. The building footprint shapefiles for all the cooling centers were read into the Colab notebook and transformed into the WGS 84 coordinate system (EPSG = 4326). Using the *contains()* method from the *geopandas* package, the point coordinates of each mobile ID were checked across all the polygons in each cooling center shapefile. The script returned relevant CSV files containing the mobile IDs in a cooling center (and the respective cooling center coordinates) from 12:00 pm to 4:00 pm.

Duration of Occupancy

To assess the duration of occupancy, we used two methods. First, we looked at the hourly variation in pings for baseline vs. hot days. In other words, we took the average of the occupancy counts across all 12:00 pm, 1:00 pm, 2:00 pm, and 3:00 pm periods separated between baseline days and hot days. Our second method was to take the ratio of unique pings to total pings for a day. We assumed that if people stayed at a cooling center longer, then their phones would ping more times. A low ratio indicates a longer duration while a high ratio indicates a shorter duration. For example, if there were ten total pings, but only five unique IDs then each person's phone pinged twice, and the ratio would be 0.5. However, if there were ten pings and ten unique IDs, then each person only pinged once, with a ratio of 1. For this analysis, we also assumed that the chance that one's phone pings is positively correlated with time. We hypothesized that people stay in cooling centers longer on hot days than on baseline days.

Using a Python script (Appendix D), we took the hourly count files, removed the N/A points, combined the data by day, then did a unique count of advertiser IDs grouped by center type. First, we took the average ratio across all the days comparing baseline versus hot by category. The second analysis shows the duration ratios (average of all center types) compared to paired hot and baseline days.

Formal and Informal Center Use

The multivariate nature of our mobility data sample required transformations of the mobile ping counts into meaningful metrics with which we can compare occupancy between the formal and informal centers. First, to assess cooling center usage while accounting for differences in cooling center building size, we divided the daily pings from each center category by the category of polygon areas in acres. This area standardization of ping per acre controls for a given center's ping frequency based on size alone. We then accounted for ping variation among the various hot and baseline sample days by dividing the subset pings by the total pings. For example, when examining hourly variation for hot and baseline days, the ping totals per hour were divided by the ping totals for the entire day. Finally, because the sample of mobility data utilized only represents 0.77-0.90% of LA County's total population, we scaled our final usage ping metric by multiplying by the 2017 LA County population. The final occupancy metric for all analyses is reported as people per acre of the cooling center building.

The primary occupancy comparisons conducted were among the formal county, formal non-county, and informal categories, as well as the variations within the categories themselves, between hot and baseline days. To assess how occupancy of center types may vary in conjunction with their spatial distributions, we also assessed how the average distance between centers of a specific category aligned with the determined occupancy; categories with lower average distances tend to have more clustered distributions of centers whereas higher average distances indicate a more dispersed distribution.

Variation in Use Between Hot and Baseline Days

To assess the variation of cooling center usage between hot and baseline days, a paired t-test was performed on usage values for three cooling center types: informally operated cooling centers, formal LA county-operated cooling centers, and formal cooling centers not operated by LA County. The paired t-test was also run for all usage values between hot and baseline days, regardless of cooling center type. Cooling center usage was measured with the same metric as for comparison of formal and informal centers, with dimensions of population per acre, and usage was calculated for each day, where the sum of pings during the study period of 12:00 pm to 4:00 pm were factored into the cooling center usage metric. The paired t-test was then performed on the mean of the differences between usage on hot and baseline days to test for statistically significant differences between the two types of days.

Results

In the following section, we present the table and maps of the cooling centers examined in our project, and the results of occupation and duration analysis. We also compare the results between formal and informal cooling centers and between hot and baseline days.

Cooling Centers

In our project, we examine a total of 1,283 cooling centers that cover a total area of 2,053.75 acres (Table 2). The locations of the cooling centers were mapped out for visual clarity (Figures 2, 3, and 4). The complete list of cooling centers can be found in Appendix B.

Table 2. Cooling Center Summary

	Center Type	Number of Centers	Total Area (in acres)
Formal County	Parks	8	2.74
	Libraries	38	18.97
	Centers	57	22.68
Formal Non-County	Parks	45	13.29
	Libraries	209	82.49
	Centers	316	118.10
Informal	Pools	84	25.40
	Recreation Centers	202	77.63
	Shopping Centers	324	1,692.45
TOTAL		1,283	2,053.75

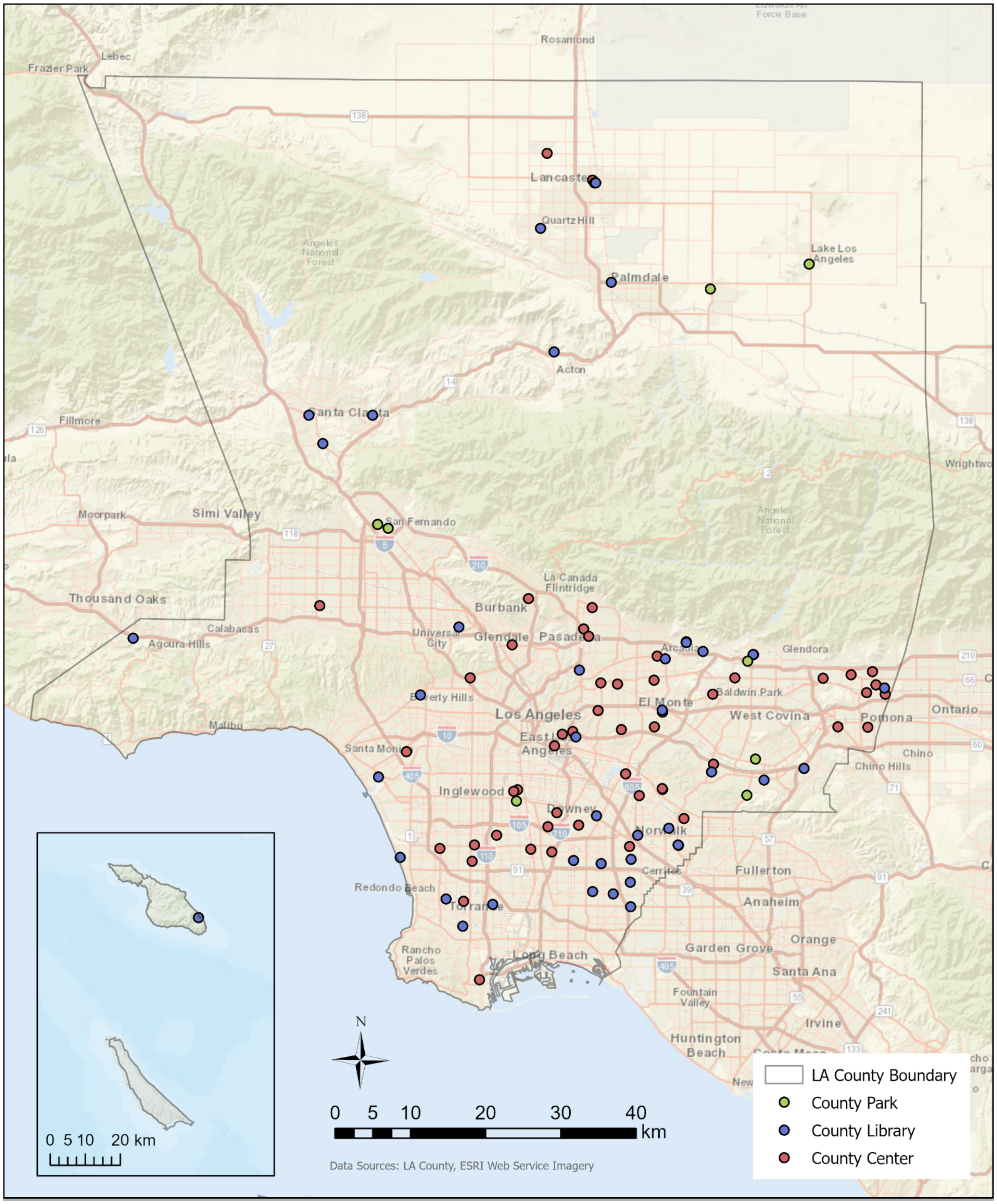


Figure 2. Formal County Cooling Centers in Los Angeles (2017)

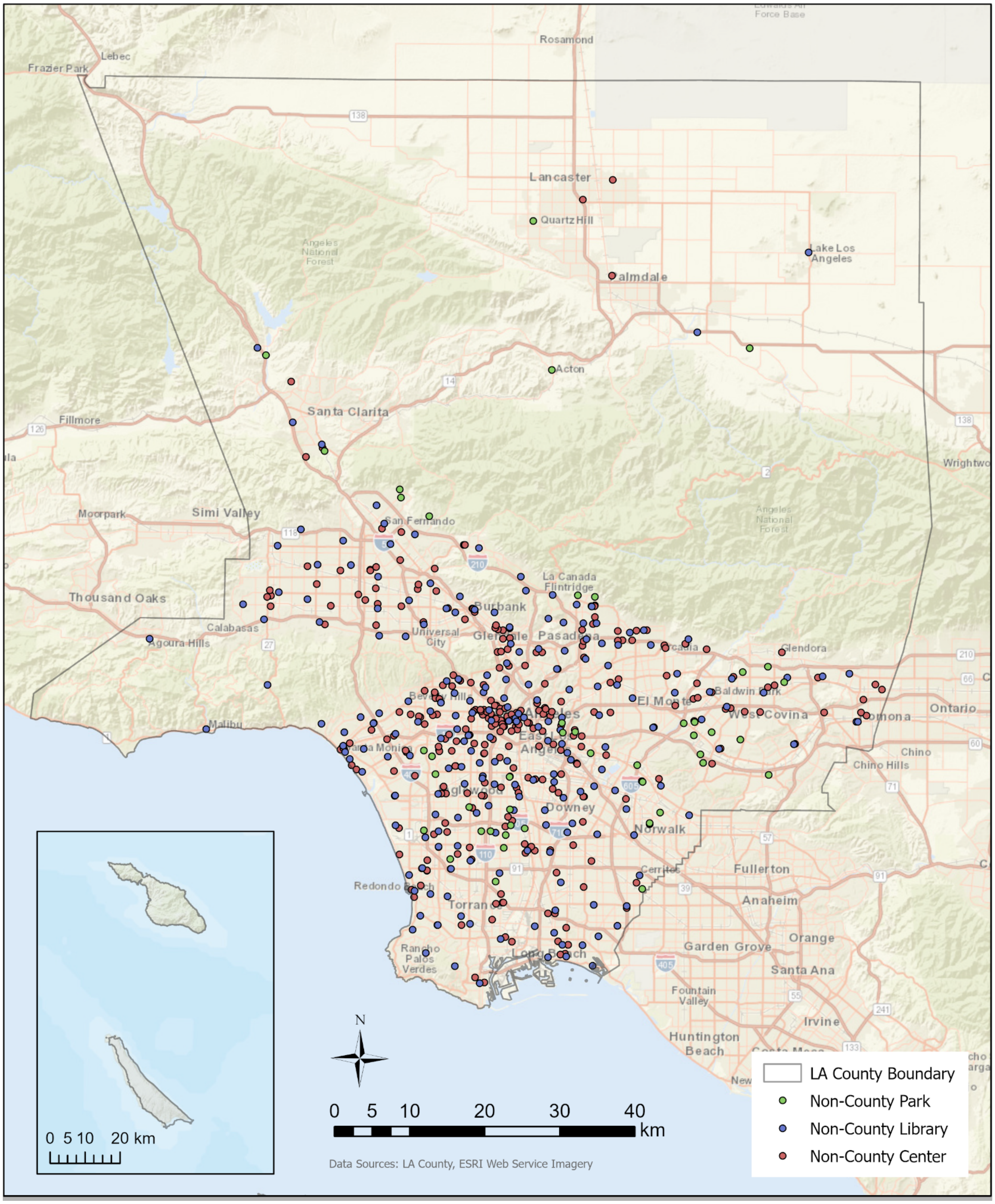


Figure 3. Formal Non-County Cooling Centers in Los Angeles (2017)

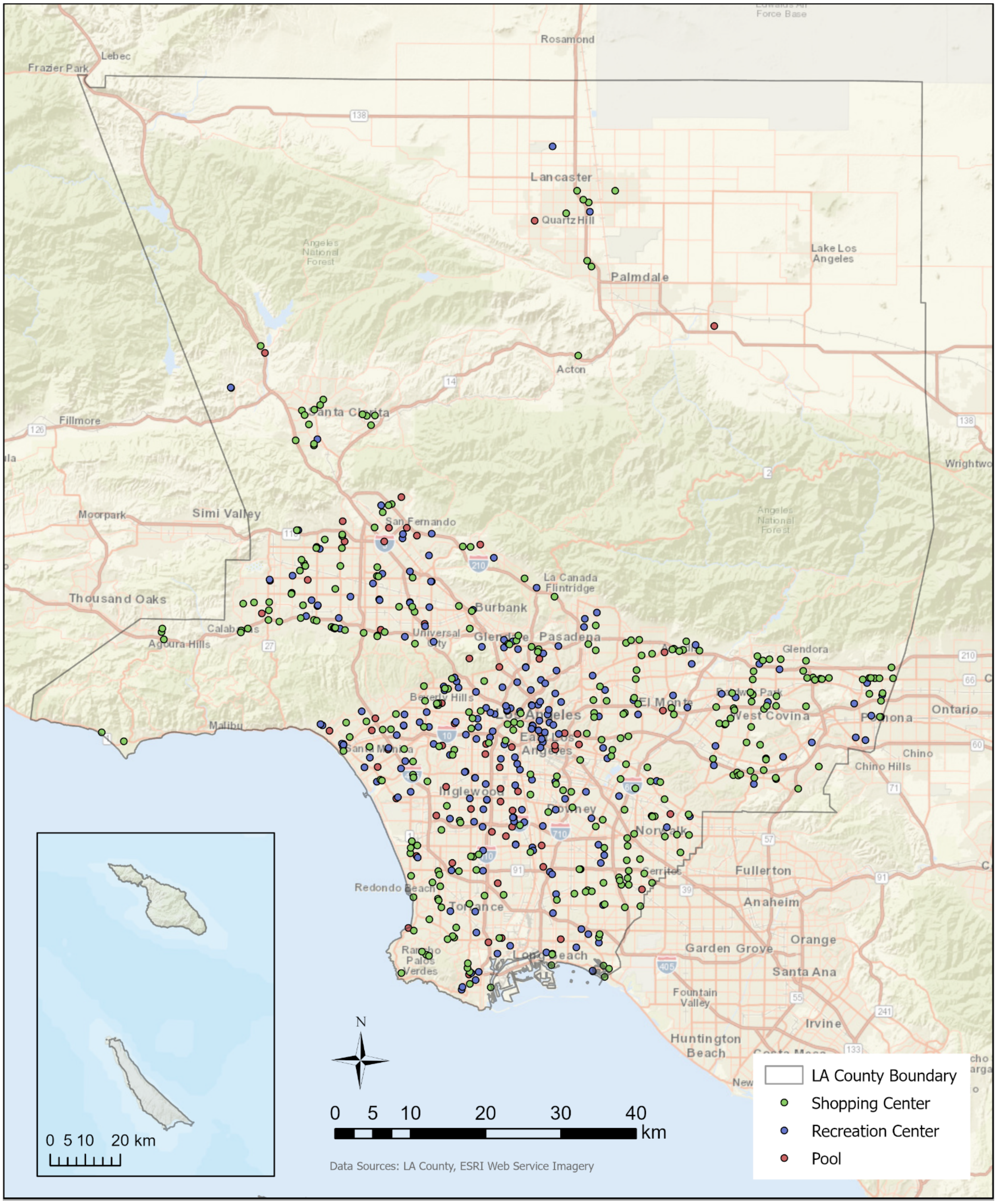


Figure 4. Informal Cooling Centers in Los Angeles (2017)

Occupation and Duration

Across all center types except parks, the average hot day has a lower duration ratio than the average baseline day, which suggests that **people are staying longer in cooling centers on hot days** (Figure 5). The data were insufficient to create a ratio for parks. Formal centers showed the greatest variance in duration ratios between hot and baseline days. As a result, we investigated the duration ratios for each pair of days for formal county centers. For all pairs except July 2 and July 9, the hot days yielded a lower ratio than baseline days (Figure 6).

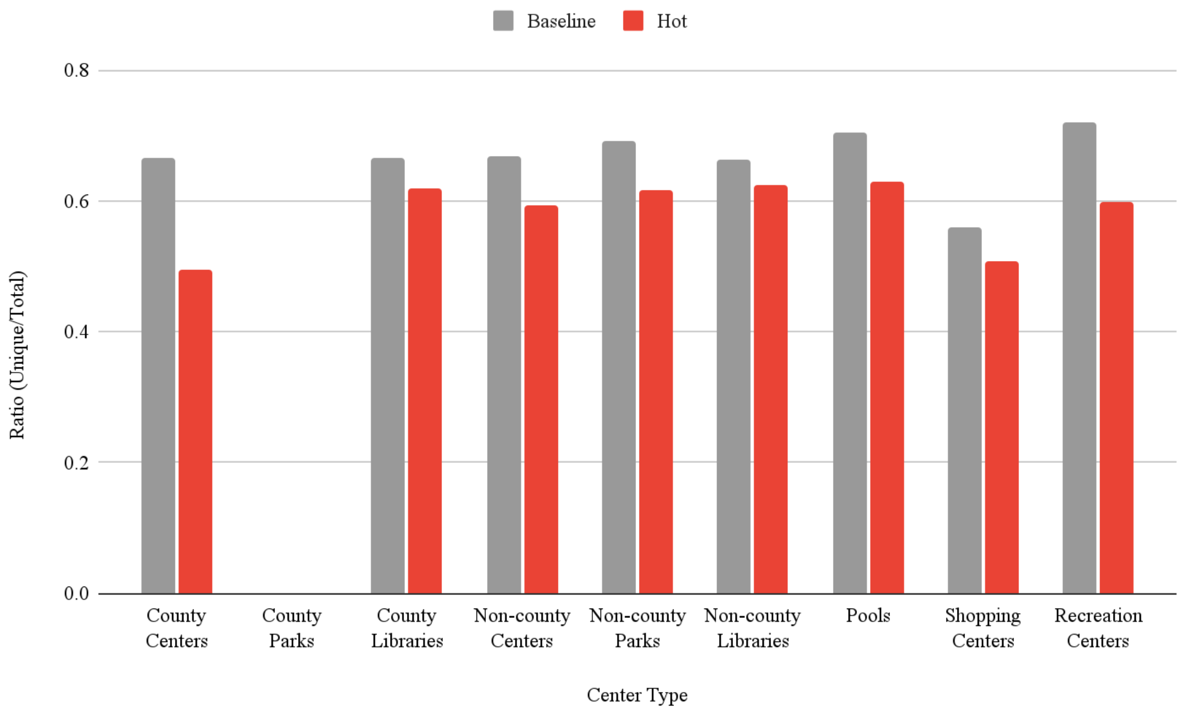


Figure 5. Duration Ratio for Average Baseline vs Hot Days by Cooling Center Type

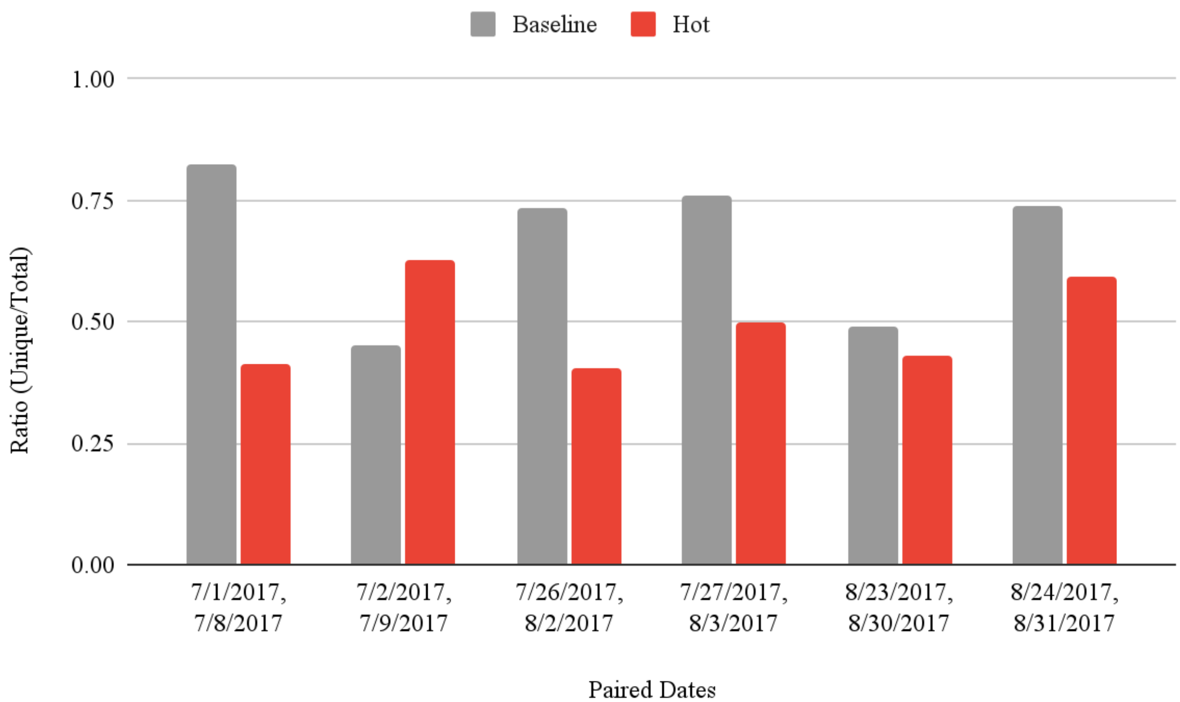


Figure 6. Formal Center Duration Ratio for Paired Hot and Baseline Days
(Note: Bottom date on labels correspond to hot days)

The occupancy of the formal county centers on hot days remained fairly consistent. On baseline days, occupancy decreased to nearly a third of the starting occupancy from 12:00 pm to 1:00 pm and continued to decline across the afternoon (Figure 7).

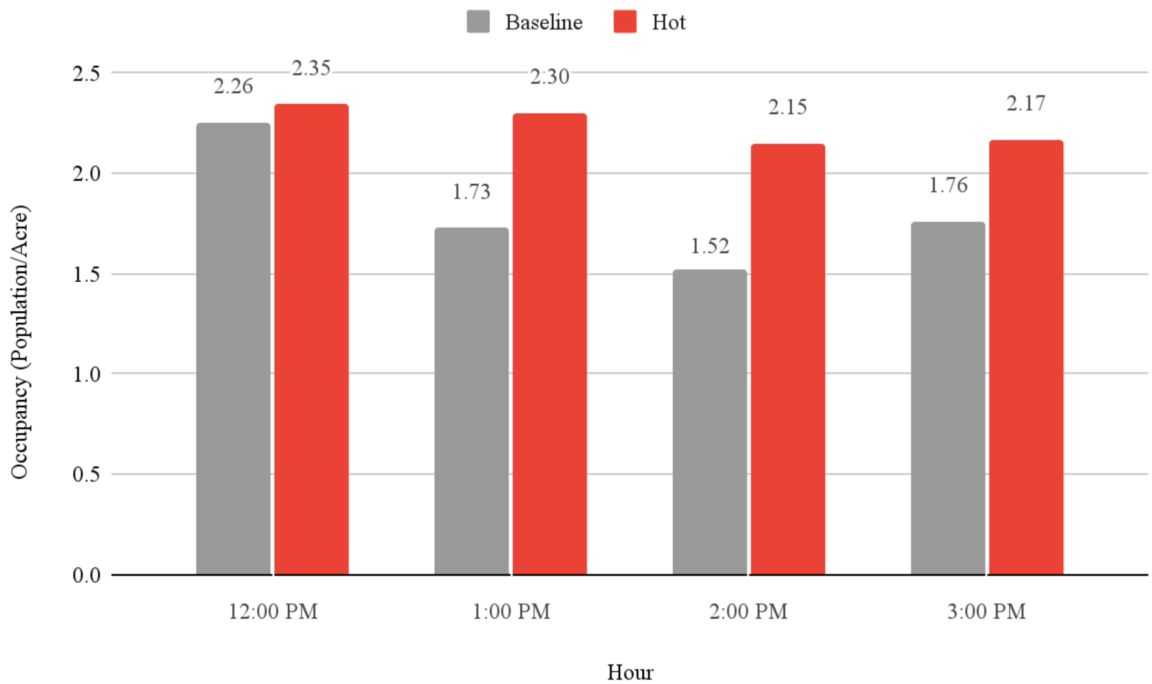


Figure 7. Average Occupancy of All Cooling Centers by Hot and Baseline Days.

Formal vs. Informal Center Use

Cooling center occupancy followed varied usage patterns both among the different categories and within the category types (Figure 8). **The average occupancy of formal county centers is relatively higher on hot days than baseline days** (Figure 8). Formal non-county centers exhibited the highest average occupancy for all days among all categories, followed by informal centers, and then formal county centers (Table 3). Table 3 also shows the lack of difference between occupancy of hot versus baseline days among our broader categories. Moreover, among informal centers, we found little change in occupancy between hot and baseline days for pools, shopping centers, and recreation centers. The informal centers also exhibited generally the smallest standard errors among the categories, with shopping centers, in particular, having the smallest standard error on hot days. Within the formal non-county category, occupancy increased for centers but decreased for both parks and libraries from baseline to hot days, similarly showing little change in occupancy between baseline and hot days.

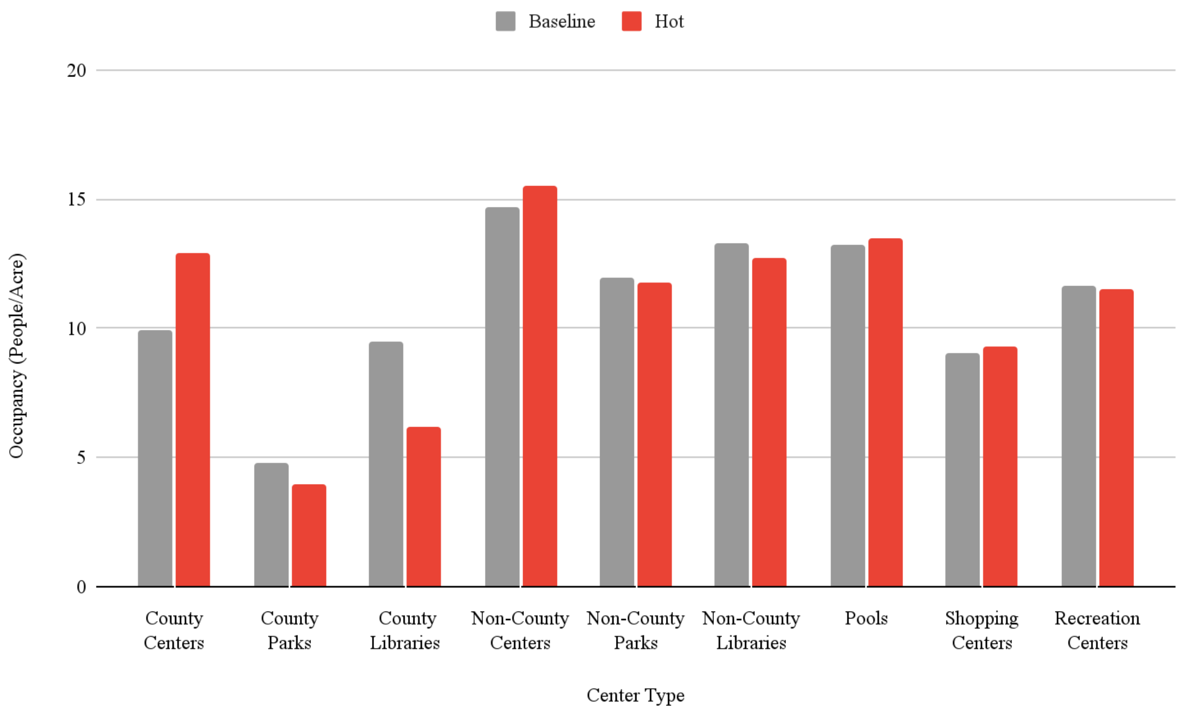


Figure 8. The Average Afternoon Occupancy of Cooling Center Types by Hot and Baseline Days

Table 3. Average Occupancy by Cooling Center Category

Cooling Center Category	Baseline (people/acre)	Hot (people/acre)	All Days (people/acre)
Formal County	8.05	7.69	7.87
Formal Non-County	13.32	13.32	13.32
Informal	11.31	11.44	11.38

The formal county category saw the greatest difference in center usage between the baseline and hot days. Formal centers showed the greatest increase in occupancy from baseline to hot days with a difference of 3.00 people/acre (Table 4). Both parks and libraries showed a decrease in occupancy from baseline to hot days, with park occupancy decreasing by 0.79 people/acre and library occupancy decreasing by 3.29 people/acre. Hot day usage of formal county libraries decreased by over a third of the usage on baseline days. Moreover, while formal centers and formal libraries saw a similar occupancy on baseline days (formal centers = 9.94 people/acre, formal libraries = 9.45 people/acre), on hot days, the occupancy of formal centers is more than double that of the occupancy of formal libraries (formal centers = 12.94 people/acre, formal libraries = 6.16 people/acre).

Table 4. Average Occupancy of Formal County Centers

Formal County Center Type	Baseline (people/acre)	Hot (people/acre)
Center	9.94	12.94
Park	4.75	3.97
Library	9.45	6.16

For the center distribution analysis, we found that formal county centers exhibited a more dispersed distribution of centers compared to formal non-county centers (Table 5), based on the greater average distance between formal county centers. Moreover, when examining facilities within the formal county category (Table 6), centers showed the most clustered distribution, whereas parks were the most dispersed, followed by libraries.

Table 5. The Distribution of Cooling Centers by Category

Center Category	Average Distance Between Centers (meters)	Standard Deviation
Formal County	3,700	5,500
Formal Non-County	1,100	1,500
All (including Informal)	630	1,400

Table 6. Average Distance Between Cooling Centers within Formal County Category

Center Category	Average Distance Between Centers (meters)	Standard Deviation
Parks	10,500	9,040
Libraries	8,130	9,160
Centers	3,580	3,500

Hot vs. Baseline Days

Both baseline days and hot days had instances of higher usage. For pairings where hot days attained a greater usage than baseline days, the difference in usage varied between 0.01 to 14.56 people per acre, and for pairings where baseline days attained greater usage than hot days, the difference in usage varied between 0.01 to 4.33 people per acre. As observed in the results above, formal county cooling centers had two of these instances of greater cooling center usage during baseline days than hot days (Figure 9). During the baseline days of July 26 and July 27, formal county cooling centers respectively attained usage metrics of 3.42 and 4.33 people per acre more than the usage during their corresponding hot day pairs. With these variations in cooling center usage and a small range of differences, the data showed no apparent pattern in usage between hot and baseline days. Accordingly, no statistically significant differences were identified in the mean difference in usage between hot and baseline days for any cooling center type during the sample period (Table 7).

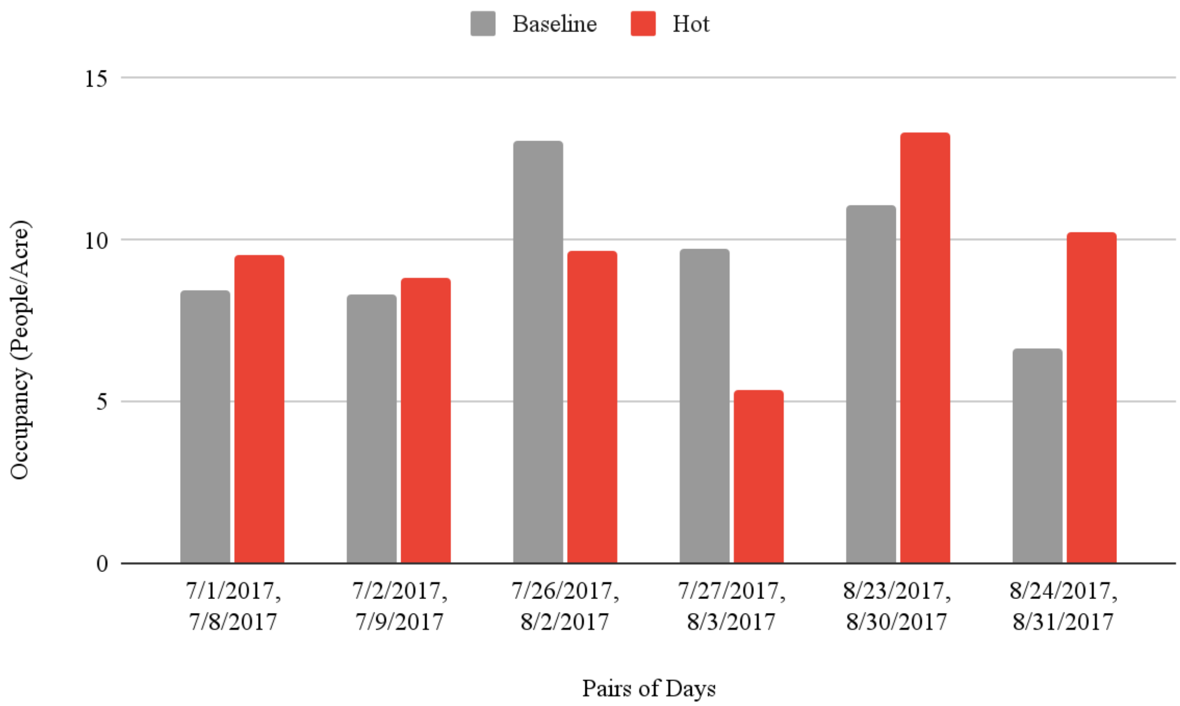


Figure 9. Formal County Cooling Center Usage of Paired Hot and Baseline Days
Note: Bottom date on labels correspond to hot days

Table 7. P-Values of the Paired T-Test Between Hot and Baseline Cooling Center Use

Cooling Center Type	p-value
Formal County	0.9639
Formal Non-County	0.9083
Informal	0.5008
ALL	0.4926

Discussion

Occupancy ratios were calculated by dividing the number of unique pings by the number of total pings for hot and baseline days, where a lower ratio suggests longer cooling center occupancy as there are fewer unique pings. The results revealed that occupancy ratios were greater on baseline days than hot days. Additionally, formal non-county centers were the most utilized centers, followed by informal and formal county centers, and cooling center occupancy was greater on both hot and baseline days among analyzed pairs of days.

Spatial and behavioral impacts on cooling center occupancy may in part explain the variations in occupancy among cooling center types. An assessment of cooling center preparation across twenty-five U.S. cities found that more dispersed cooling centers tend to provide greater population coverage and therefore greater access to cooling centers generally (Kim et al., 2021). While we found that formal non-county centers saw the highest occupancy between both hot and baseline days (Table 5), formal county centers exhibited a more dispersed distribution of centers than formal non-county centers. Moreover, when examining the formal county category (Table 6), although centers showed the highest average occupancy, they also showed the most clustered distribution of centers.

The unexpected mismatch in clustered distributions showing higher occupancy for our sample may point to the influence of user perception affecting occupancy. **That is, even if parks and libraries may provide more population coverage than centers, the perception of a given facility by the sampled users may detract from the increased accessibility provided by larger population cover.** Indeed, Sampson et al. found that in a survey of potential cooling center users, respondents voiced concerns over what they would do at centers, hesitations over traveling to an unfamiliar place, and questions as to whether or not they would be sitting in a place with nothing to do (Sampson et al., 2013). With libraries, for example, the decreased occupancy on hot days compared to both baseline occupancy and center occupancy on hot days may reflect notable impacts from user perception, in addition to accessibility impacts discussed in Chapter 3.

Cooling center occupancy generally did not observe a clear pattern in occupancy between hot and baseline days, as supported by negligible cooling center occupancy for informal centers, decreases in occupancy from baseline to hot days in formal parks and libraries, and the lack of significant differences in usage for day type pairs. However, the increased occupancy between baseline and hot days for formal county and non-county cooling centers of the study sample, though not statistically significant, may suggest that cooling centers are in use. The greater changes in occupancy between hot and baseline days within the formal county category compared to the formal non-county and informal groups may suggest a more discriminating use of the formal county centers for cooling purposes by the sampled users. The comparable visitation of informal and formal non-county centers between hot and baseline days may suggest that users are not using these centers for specifically cooling purposes, but rather are using the facilities for their normal purpose. As the cooling centers in this study are mostly public facilities that serve other functions beyond providing air conditioning, such as acting as shopping centers or providing services such as the internet, usage of these facilities may be already integrated into the daily or summer behavior of the individuals tracked in the sample. This suggests that among the sampled users of cooling centers, and the selected extreme heat events, increased temperature was not an influential factor in cooling center usage.

Occupancy alone, between hot and baseline days, did not reveal a clear pattern, but occupancy duration changed in relation to temperature. In this study, lower occupancy ratio was a reflection of more consistent usage throughout time, where the same pings (and thus patrons) would be accounted for, as opposed to a larger number that suggests that different people move throughout the center. The lower daily occupancy ratios found for hot days in comparison to baseline days indicates that patrons stay in cooling centers for longer periods of time than during baseline days. As this pattern was observed for both formal and informal centers, patrons use an array of cooling center types as a way to escape the heat. Analysis of combined cooling center occupancy in terms of people per acre further supports more consistent and prolonged occupancy of the centers on hot days compared to baseline days, it was relatively consistent for the four hours of the hot days, while decreasing for three of the four hours.

Although mobility data has the ability to track patrons at more precise spatial and temporal scales to provide insight on occupancy, it is also limited in distinguishing among user information that may influence the occupancy analyses. Employees and other individuals who help operate these facilities may have also been pinged regardless of temperature, which could reflect the similar numbers in usage across hot and baseline days. The nature of using mobile phones as a proxy for human tracking also results in an underrepresentation of certain groups who may not have mobile phones that can be tracked in cooling centers, which could reduce the number of users in cooling centers on hot days. In Los Angeles for example, a study among a sample of homeless individuals in Los Angeles showed that approximately 66% owned a smartphone that had internet access, and the estimate of low-income individuals that owned a smartphone with internet access in the United States was 67% (Galperin et al., 2020). Nevertheless, as with survey-based methods of data collection, sample limitations are to be expected when users consent to being tracked through mobile applications, and big data, with many repetitions, can minimize confounding variables.

Chapter 3. Vulnerability Analysis

Variance in socio-economic status leaves some individuals more vulnerable to heat-related health risks. The distribution of cooling center locations in LA County and knowledge of cooling resources is essential to supporting vulnerable populations during extreme heat events. In this chapter, we will discuss heat vulnerability and social sensitivity of LA County residents while exploring demographic characteristics of cooling center users.

LA County contains a unique demographic array of individuals with a variety of socio-economic attributes. It is also susceptible to heat-related risks as an urbanized environment with a Mediterranean climate, ultimately making it a critical area for study to address urban heat-related public health risks. Although Mediterranean climates are characterized to have exceptionally hot, dry summers, the presence of warm and dry winds in Los Angeles, known as the Santa Ana winds, pose a threat to heat-vulnerable populations in the winter (December, January, February) as well (Wheeler et al., 2019). Elderly individuals aged sixty-five and older have a significantly greater risk of heat mortality during winter months in Los Angeles as a result of these winds (Kalkstein et al., 2018). Thus, heat-related risks in Los Angeles are not merely a seasonal issue, but year-round for vulnerable populations.

Studies of social vulnerability in the context of natural hazards have long established the susceptibility of suffering harm from hazardous events based on certain socio-economic conditions (Cutter et la., 2003). Several heat-related vulnerability assessment schemes have been developed in recent years (Reid et al., 2009; Harlan et al., 2013). Los Angeles also contains groups that are more at-risk for heat-related illnesses and deaths than others. Outdoor workers in LA County, specifically construction workers and agricultural workers, have a greater number of visits to emergency departments (Riley et al., 2018). This increased risk is due to several factors, such as prolonged exposure to outdoor heat, use of protective clothing that intensified heat retention, and inaccessibility to facilities with cooling technology (Riley et al., 2018).

Where such occupations loosely correlate to lower socio-economic status, it is apparent that lower socio-economic status contributes to higher heat-related health risks. Furthermore, minority communities, particularly Non-Hispanic Black and Hispanic communities, all exhibited increased heat-related health risks in Los Angeles (Mitchell & Chakraborty, 2015). The same study found that people with disabilities also had increased heat-related health risks, and populations with a higher proportion of high school graduates had lower risks, but the strongest correlations to heat-related health risks were with household income and homeownership in Los Angeles (Mitchell & Chakraborty, 2015). Based on the index used in this study, all of these groups were at a disproportionately higher risk of heat-related illnesses due to factors including limited access to urban vegetation and concentration in areas with denser urban infrastructure or heat-prone areas such as the High Desert. Thus, socio-economically disadvantaged areas in Los Angeles have less resilient infrastructure and urban design for heat risks.

In addition to these broad urban and environmental circumstances, an individual's risk perception of health hazards is also informed by personal experience and the information made available to them (Ferrer & Klein, 2015). One key finding from an investigation of the reasoning behind individuals' adoption of health-promoting behavior relays how vulnerable individuals' view of themselves within their larger community influences their risk perception (Sampson et al., 2013). Lack of awareness regarding individual health risks to extreme heat compared to their neighbors indicated an increase in heat vulnerability.

Along with vulnerable individuals' potential to underestimate their own health risk, external social factors, such as distrust of local authorities, may deter how readily individuals adopt safety and cooling behaviors (Sampson et al., 2013). These deterrents have important implications for how governments administer resources and funding into heat management plans; even if resources exist and their benefits are well communicated, their usage by those most vulnerable may be undermined by individuals' wariness of using those very resources.

A deeper understanding of these factors that affect an individual's heat risk perception can also allow extensive insight into their greater community's social vulnerability. Social vulnerability, as defined by the LA County Climate Vulnerability Assessment, is "the susceptibility of a group or population's ability to prepare, respond, and recover from exposures, harms, or hazards" (LACCSO, 2021, p.120). These conditions can vary widely between census tracts and include but are not limited to: differences in infrastructure, economic class, social services, health status, age, ability, and political power (LACCSO, 2021).

For the purpose of this study, we use Los Angeles County's 2021 social sensitivity index (SSI), as a measure of underlying social vulnerability. This SSI uses 29 indicators and evaluates the social sensitivity to climate hazards as part of developing a vulnerability assessment in combination with hazard exposure.

LA County's methodology for SSI is based on similar assessments and established methodologies, to select and analyze twenty-nine socio-economic indicators that influence a community's response to climate hazards (LACCSO, 2021). These indicators are in ten broad categories: age, community and language, education, health, housing, income and wealth, occupation, transportation, access to information, and race/ethnicity. The selected indicators represent characteristics that are associated with increased sensitivity to climate hazards, or may relate to resilience , or the communities' preparedness and recovery ability in relation to climate hazards. This social sensitivity index is a valuable tool in geographically visualizing the inequities between communities and determines a degree of susceptibility to suffer harm that can be used to improve community responses before, during, and after hazard events. This section of our project explores this tool and its capacity in relation to the cooling centers we are examining. By first locating the distribution of cooling centers in Los Angeles County, we can use the SSI as a rough estimate to identify the demographics of users that are serviced by the centers of interest. An analysis of who uses these cooling centers provide significant implications for how to better service these populations. Most importantly, identifying the most vulnerable populations can aid public health initiatives to improve community response during extreme heat events.

In this chapter, we therefore address the following research questions:

- What is the overall distribution of formal and informal cooling centers in the County of Los Angeles?
- What is the feasibility of using mobility data to infer demographic characteristics and spatial origin of users of formal and informal cooling centers during extreme heat events compared with baseline use?
- How can cooling center usage be encouraged?

Methods

In this section, we review the methods of our vulnerability assessment. First, we explain how we found the SSI tract of cooling centers. Next, we will explain how we obtained user location for the purpose of capturing user SSI tract. Finally, we explain how we conducted cooling center staff interviews.

Cooling Center Location

We begin with identifying the locations of cooling centers to assess which communities they serve. This will help identify mobility patterns of centers in differing SSI tracts in the number of visitors and the distance traveled by users. To identify which tract our observed cooling centers were located in, we took the initial point layers of all the center locations and overlaid them atop the SSI tract layer. The SSI tract layer was provided by the clients and is congruent with the SSI classifications in the Los Angeles Climate Vulnerability Assessment. The overlay was used to create our maps. The other deliverable consists of summary tables. This was achieved by further processing of the layers in our maps by using ArcGIS Pro's *spatial join* tool which intersects the cooling center points to the SSI tract polygons. The joined layer containing the center ID, its coordinates, and its SSI third score was exported as a CSV file for graphical visualization use in google sheets. Pivot tables provided the final summary tables that are represented in our bar graphs. The final output communicates the distribution (through counts) of each type of cooling center for each category of tract vulnerability.

User Location

To address the gap in understanding cooling center users, we analyzed the spatial origin of center users by tracking their ID back to their nighttime resting location. This was done by continuing to subset the data using Python. In the original processing, we were able to determine the count of visitors to different types of cooling centers; the IDs of those users during the day were extracted and then matched (if possible) to a ping at nighttime. This ping's location was saved and correlated to the social sensitivity of the tract, taken to be the original demographic of the user. These locations were put into a data frame and exported out to a CSV file by day.

Afterward, we combined the resting locations of users into files sorted by the type of center they visited and by type of day (baseline or hot) on google sheets. This resulted in some duplicate IDs who kept reappearing and going to the same center, likely an indication of worker status and their daily commute. Afterward, some processing using the Google Sheets *left()* function had to be done to extract a joinable index from the center description. The result was 18 CSV files sorted by day type and center location by center_id. The CSVs went through processing in ArcGIS Pro to be joined to the center polygon layers, matched via the CSV center-index and the polygon layer FID field. Each user ID was reassociated to a center, and the average sensitivity score of each center's visitors was calculated. While summary statistics could be calculated in ArcGIS, Python also provides a convenient *groupby()* method through the *numPY* package where it automatically returns the sensitivity score of the users by center type. Boxplots made on Python using the *seaborn* package were chosen to visualize this relationship.

Interviews

While quantitative mobility data reveals the overarching patterns and trends of cooling center use, qualitative case studies may better elucidate the direct experiences and perspectives of individuals who operate cooling centers to explain the patterns observed from quantitative data analysis (Verhoef, 1997). Moreover, given the noted potential for uneven sampling from mobility data, qualitative analysis of cooling center occupancy may help explain the occupancy differences observed amongst different subpopulations. As such, we completed a case study of cooling center use in the San Fernando Valley/Pacoima region by conducting interviews with employees of select cooling center locations in this neighborhood. We chose this region as it has been identified by LA County as a region of high social vulnerability (LACCSO, 2021) facing some of the most severe heat events in the county (Wang & Lu, 2021). We chose a variety of center types for phone interviews, which included two formal county and ten formal non-county centers (Table 8). Informal centers were not chosen because they do not officially operate as cooling centers, thus employees of these centers may not know or observe patron occupancy and behavior on particularly hot days. The phone interviews were planned for 30 minutes and included questions regarding the operations for opening as a cooling center, observations of patron behavior when activated as a cooling center, additional resources provided by the center on hot days, and transportation access.

Table 8. Centers Contacted for Interviews in the San Fernando/Pacoima Region

Center Name	Category
San Fernando Recreation Park	County Park
Las Palmas Park	County Park
Youth Speak Collective	Non-County Center
San Fernando Library	Non-County Library
San Fernando Valley Interfaith Council Nutrition Program - Sunland Senior Center	Non-County Center
Northeast Valley Multi-Purpose Senior Center	Non-County Center
Pacoima Branch Library	Non-County Library
Sunland-Tujunga Branch Library	Non-County Library
Valley Village - Sunland Adult Day Health Care Center	Non-County Center
Mid-Valley Senior Center	Non-County Center

Results

The following section reviews the results of the vulnerability analysis including maps and graphs of social sensitivity tracts and interview responses from cooling center operators.

Cooling Center Location

We were concerned with understanding the spatial distribution of centers to help inform some of our findings. Exploring cooling center characteristics only required the use of ArcGIS to map and report summary statistics. In our visual investigation of cooling center services (Figure 10), we found that the breadth of coverage seems to cluster around certain regional areas (confirmed using the *Average Nearest Neighbor* tool in ArcGIS (Appendix J); implications of these distributions are further discussed in Chapter 4, which analyzes distances to resting locations). By total counts, formal county and non-county centers are by far located in more high vulnerability tracts (high SSI) **(**Figures 11 and 12). The service area then may reflect the county's intentionality in providing services to populations who need them most. County and non-county parks and libraries do not reflect this. Instead, only 26% of non-county libraries and only 34% of county libraries are located in high vulnerability areas. Specifically, the number of non-county libraries in high SSI tracts is much less than the number in low and moderate SSI tracts (Figure 12). This is a significant oversight given the importance of libraries for social services, and for the scope of our investigation: escaping heat. Facilities in parks constitute an inconsequential part of the plan for mitigating heat exposure for our methodology. Rather, we found that a great majority of facilities in parks actually constituted the formal center layer and were considered as such. Of the remaining facilities in parks, we find that using mobility data to track usage of these building facilities for heat mitigation is currently infeasible and out of scope as we would have to find a way to measure the difference between usage of facilities with finding slight reprieve through shade and evapotranspiration.

When comparing the number of the formal centers, both county and non-county (Table 9), we found a comparable number of formal centers to informal centers (673 formal versus 610 informal centers). This absolute count obscures the fact that the total building footprint area of informal centers (largely the shopping centers) is much greater than the footprint of the formal centers. **With the building footprint taken into account, informal centers encompass a much larger catchment of visitors during our study period due to the greater area of buildings in this category.**

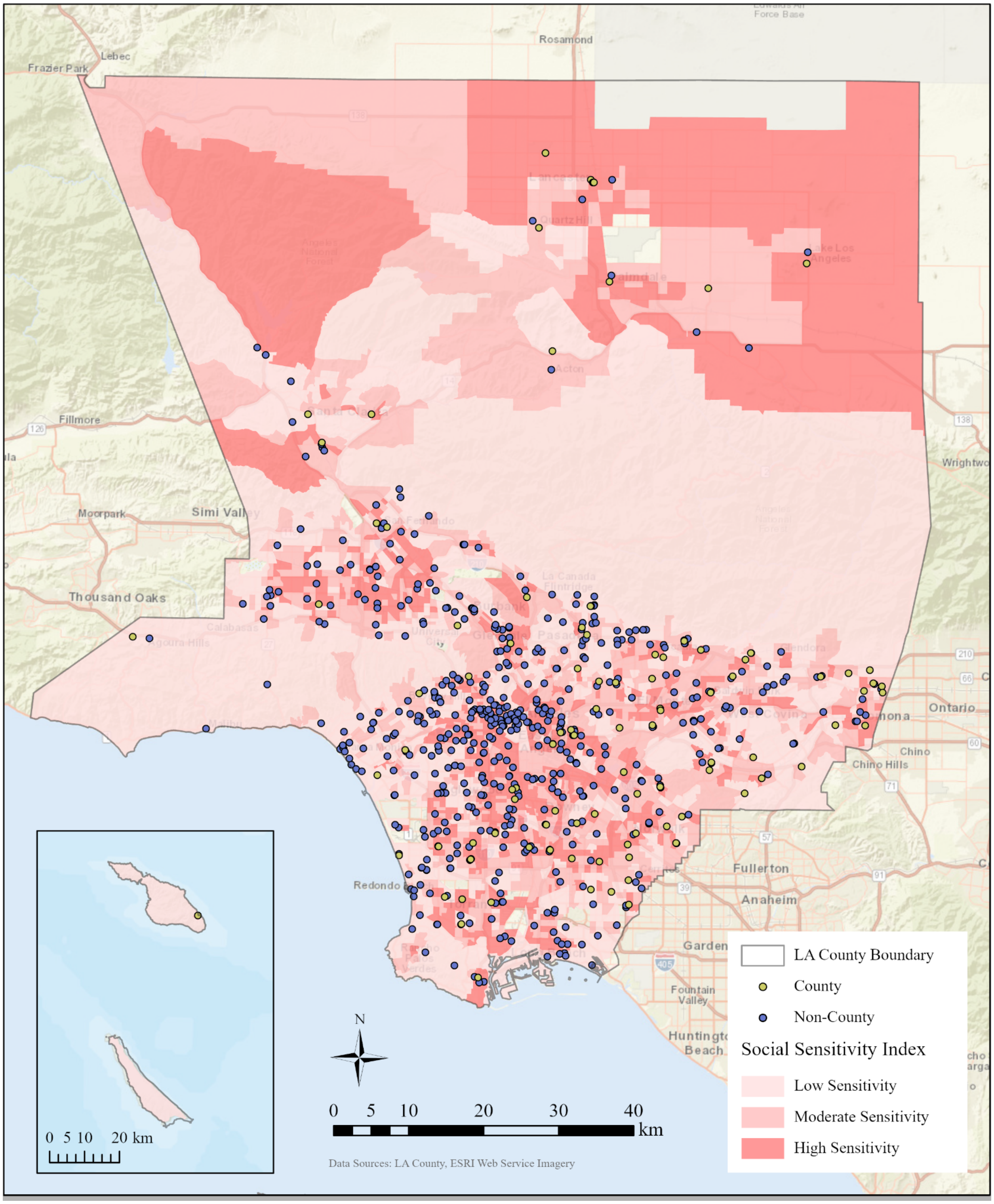


Figure 10. Formal County and Non-County Cooling Centers and SSI Tracts in 2017

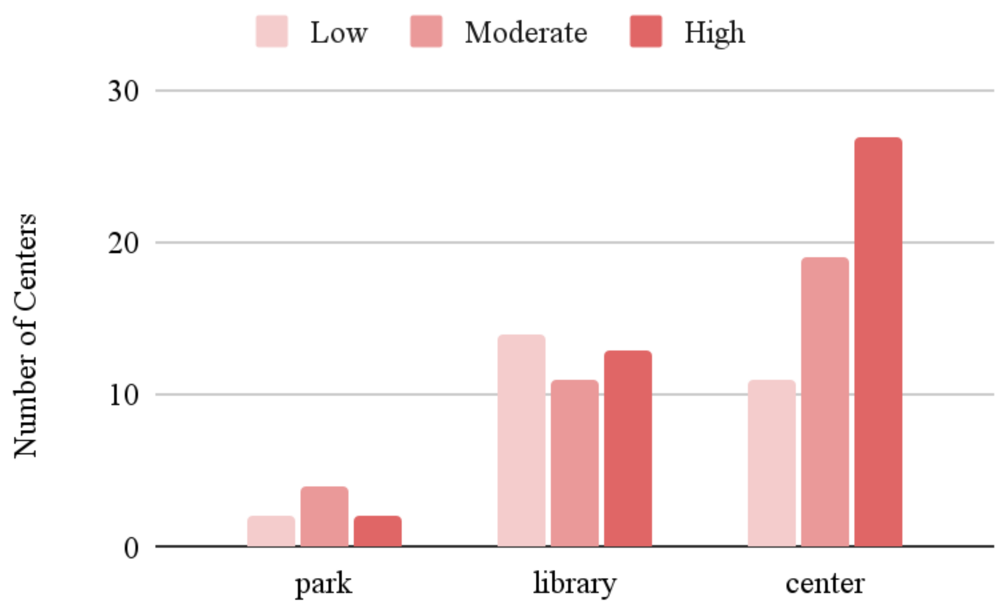


Figure 11. Formal Cooling Center Counts by SSI Thirds

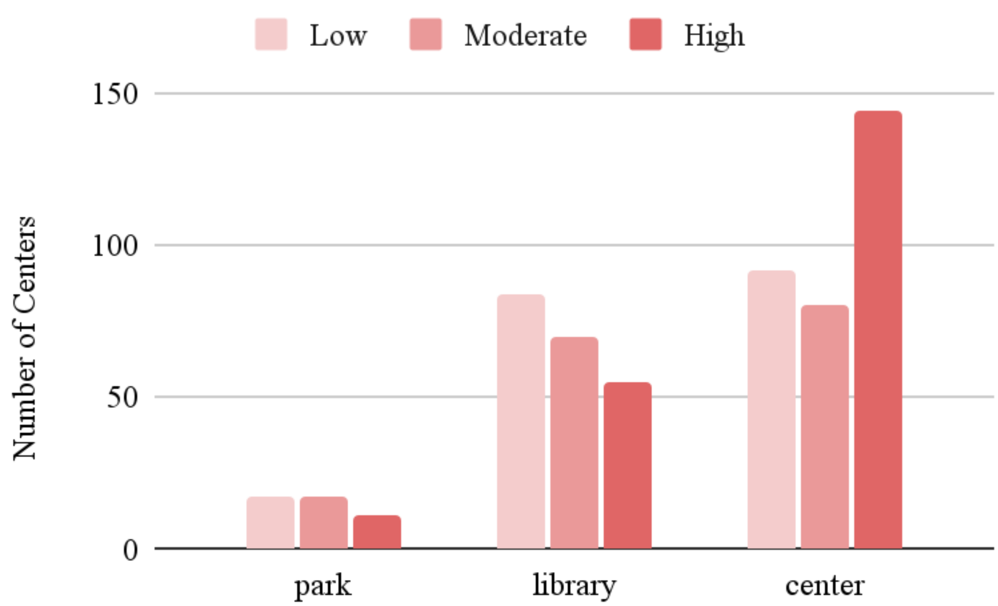


Figure 12. Formal Non-County Cooling Center Counts by SSI Thirds

Table 9. Number of Cooling Centers Located in Each SSI Third

		SSI Third			
		Low	**Moderate**	**High**	**Total**
Formal County	**Park**	2	4	2	8
	Library	14	11	13	38
	Center	11	19	27	57
	SUM	27	34	42	103
Formal Non-County	**Park**	17	17	11	45
	Library	84	70	55	209
	Center	92	80	144	316
	SUM	193	167	210	570
Informal	**Pool**	21	32	31	84
	Recreation Center	62	54	86	202
	Shopping Center	123	121	80	324
	SUM	206	207	197	610

User Location

For formal county cooling center facilities, we found that they had a slight tendency to be used by the same demographic that they served based on location with only a discernible difference in center user demographics between baseline and hot days for cooling centers in the most vulnerable tracts (Figure 13). **Formal county libraries showed a clearer increase in the number of more vulnerable users on hot days as the median average demographic SSI of the users increased for each group of library locations.** Formal county libraries also tended to serve their demographic population where less vulnerable people visited libraries in low SSI tracts and more vulnerable users visited libraries in more vulnerable tracts (moderate and high SSI). For parks, we could not make any meaningful observations or discussion, as the number of users captured was too small.

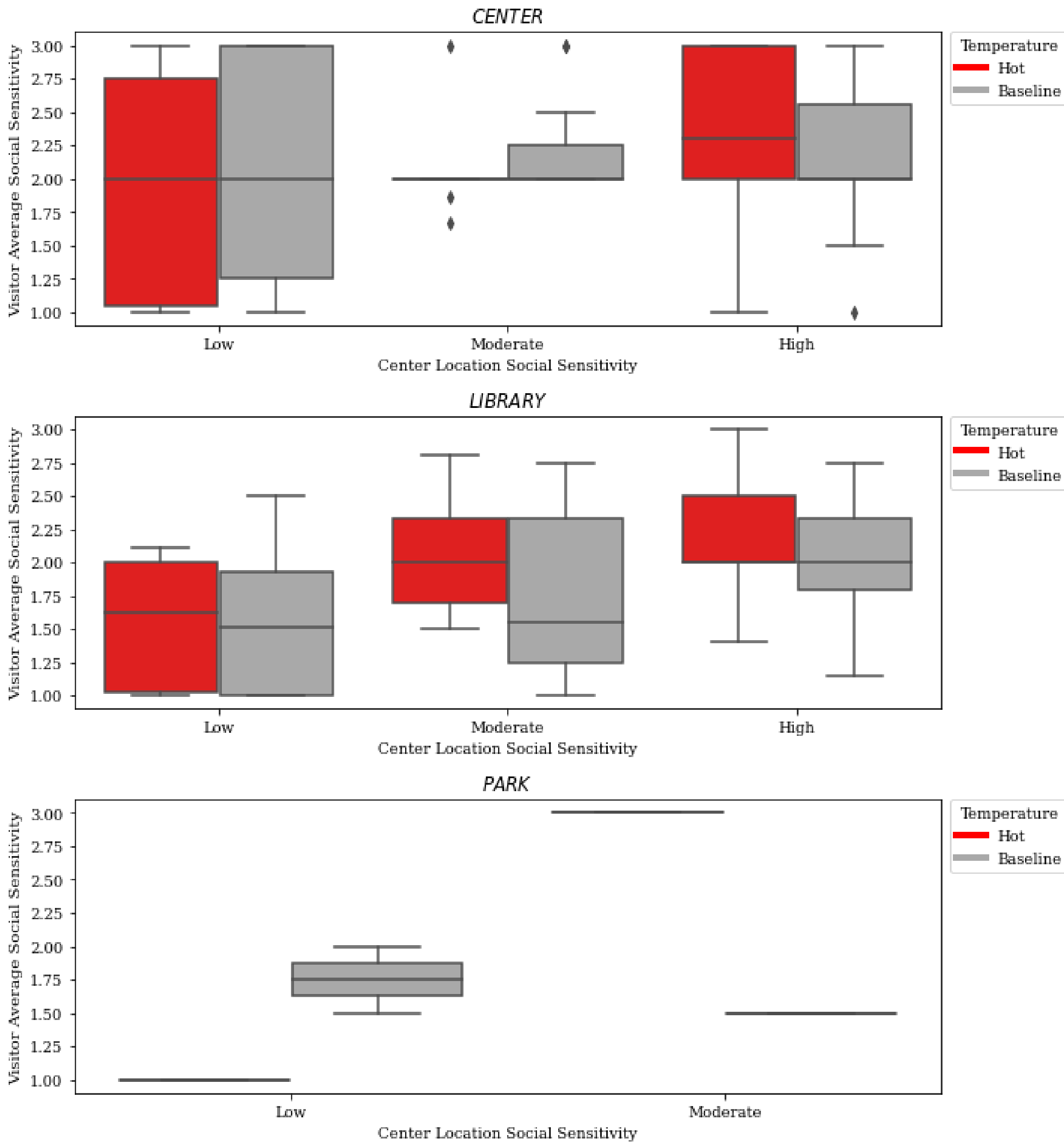


Figure 13. Demographics of Formal County Cooling Centers Users

Non-county facilities exhibited clear differences in users between baseline and hot days (Figure 14). Non-county cooling centers served the same demographic populations as their tract location. On hot days, the average demographic of the users increased, which may indicate that the non-county facilities are visibly being used as a cooling facility by vulnerable populations. Non-county libraries exhibit a distinct usage pattern between the library's location SSI and the user's average SSI. In libraries located in moderate and high SSI tracts, there were more vulnerable users on hot days (increased median), while the libraries in low SSI tracts saw a slight decrease in high vulnerability users. Non-county park facilities saw an increase in usage by highly vulnerable populations on hot days, though this observation is limited again by the small catchment of users (number of users in hot days = 9, number of users in baseline days = 11).

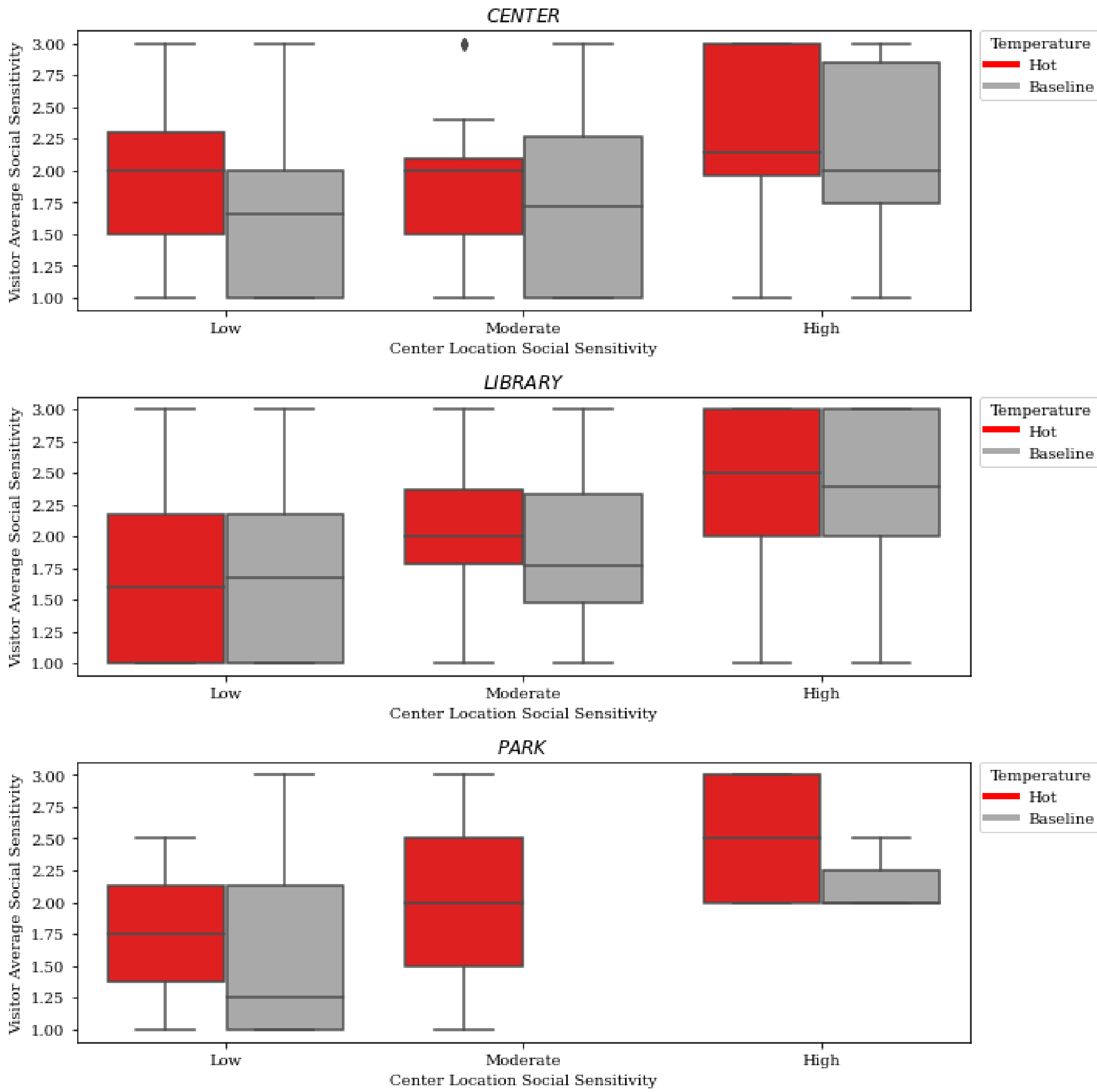


Figure 14. Demographics of Formal Non-County Cooling Centers Days Users

For the last set of informal cooling centers, many of the same trends held true and supported our initial postulates (Figure 15). The service zones of informal centers remain predominantly tied to their locations, though visitors from all different social vulnerability tracts were observed. This is reasonable and expected as "high-end" shopping centers like Rodeo Drive or The Grove are located in low vulnerability tracts and service low vulnerability populations. **During heatwaves, shopping centers in high SSI areas saw an increase in high SSI users. Similarly, for recreation and pool facilities, member demographics were often community focused rather than broad serving.**

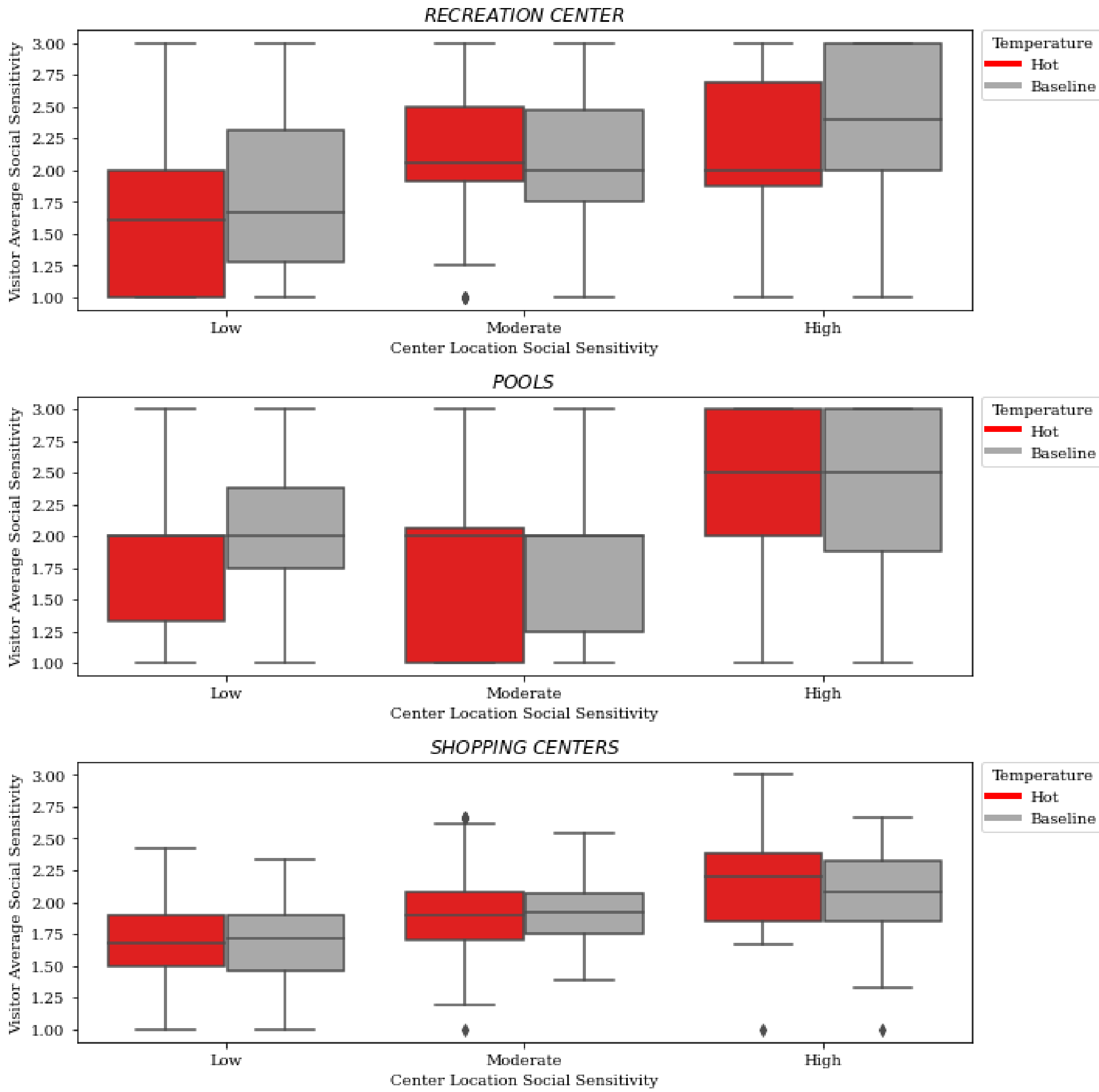


Figure 15. Demographics of Informal Cooling Centers Users

Interviews

Out of the twelve centers contacted, only two were available for phone interviews, which were both formal non-county libraries. Upon contacting the centers for interviews, many staff members were not aware of their facility's cooling center status and declined or were unable to speak to how their cooling center operated. The overwhelming number of declines received for interviews (8 out of 10) suggests that cooling center awareness may be lacking even among formal centers, not just informal. The completed interviews (Appendix I), however, provided important observations of cooling center patron behavior and barriers to cooling center usage. Due to our very limited sample, our case study results are unique to libraries, specifically, non-county libraries. These results do not help explain the quantitative results for other center types.

The formal non-county libraries activate as cooling centers when the directive is received from council members, the County of LA, or the City of LA. The libraries then release information via social media; no physical signage is placed on the doors or windows of the buildings to avoid information overload. One interviewee noted that they *think* this information is also posted on the library's website but were not completely sure. When activated as a cooling center, patrons typically spend their time on computers, laptops, phones, or reading books; one interviewee noted their facility also provides bottled water for patrons. Both interviewees noted that the cooling center patrons are generally representative of the community in terms of racial and socio-economic demographics. Both facilities also have bus stops in front of the building or very close to it; while it was observed to be a popular way to reach the facility, the transportation users may also reflect the strata of cooling center users in that people with cars or houses may not need to travel to a different location for cooling purposes.

Discussion

By total counts, formal county and non-county centers by far are located in high vulnerability tracts which may reflect the county's intentionality in providing services to populations who need them most. The number of non-county libraries in high SSI tracts pales in comparison to the number in low and moderate SSI tracts (Figure 12). Libraries in high SSI tracts may fall in unincorporated areas of the county which were not analyzed.

There was an observed increase in average user vulnerability on hot days in high vulnerability tracks for 7 of the 9 cooling center types. This implies that on hot days, cooling centers serve a more vulnerable population on average than on baseline days. Slight decreases in non-county library usage on hot days among people from higher vulnerability tracts may be related to heat exposure from traveling to cooling centers. Aspects of travel, such as long walking distances in the sun and a lack of shading at bus stops, drastically affect people's choices in using a cooling center (Nayak et al., 2019). As such, vulnerable populations may be less likely to visit faraway facilities when the temperature is unbearable in an effort to avoid intermediate heat exposure or discomfort. Still, the increase in vulnerable users at non-county libraries emphasizes the need to increase the number of these facilities in tracts of high vulnerability, as we noted in Chapter 3.

Informal cooling centers had mixed results that partly suggest that people of higher social vulnerability use cooling centers more during hotter days. On hot days, shopping centers in high SSI areas saw an increase in high SSI users, which could have likely been composed of populations who may not have cooling infrastructure at home and sought reprieve elsewhere. Conversely, the decreased average SSI of users from baseline to hot days in recreation centers may be a result of behavioral anomalies, as potential barriers such as monetary membership costs do not fully explain the situation, given the relatively high usage on baseline days. The pool usage in low SSI tracts during heatwaves suggests that more vulnerable populations do not travel far to use these facilities in heat as the average SSI of pool visitors decreased (more visitors from low SSI).

The most prominent barriers to cooling center usage are the limited avenues of information dissemination, which may hinder the accessibility of cooling centers to vulnerable populations in particular. By only using online advertising methods, populations such as the elderly or individuals experiencing homelessness who may not have access to or use the internet regularly may be entirely missed in advertisement methods. In finding that non-county cooling centers service the same demographic populations as their census tract location, this barrier of information dissemination may have compounded impacts for libraries servicing a majority high vulnerability community. This follows an interviewee's observation that only patrons who frequent the center regularly know that the facility operates as a cooling center, so non-regular patrons may not be aware of this resource. Indeed, throughout the entirety of the library operating as a cooling center, one interviewee noted that only one or two people have called to inquire about using it for cooling purposes. Thus, diversifying advertisement methods to alleviate the digital divide may increase cooling center user engagement among groups that are also at higher risk of health complications from extreme heat.

Underlying all of this data is a caveat regarding sample size. Despite the initially large dataset, after subsequent subset processes, we were left with a small number of users located over our six pairs of days. This is noticeable in the county parks, where no users were located in parks in moderate SSI tracts for either baseline or hot days Similarly, there was no user data for baseline usage of non-county parks in moderate SSI tracts. In the future, a larger number of data pairs would be preferred, such as looking at the entire Los Angeles summer and early fall for 2017. A larger sample size would expect to yield box plots with more prominent differences in the median between baseline and hot days, as well as reduce the spread of values. Additionally, some processing issues occurred in which due to an unforeseen event of identical center names but different locations, some of the average SSI of the users were related to the wrong center. We had chosen to remove these centers with identical names to prevent errors in the final user SSI average.

It must also be noted that we have assumed that a center user's resting location (between 1 to 4 AM) would be their home and therefore equate to their sociodemographic characteristics. We recognize that this proxy for determining a user's demographic information may result in unreliable results, such as for the unhoused and legally homeless who may have dynamic living conditions. However, with the imperfect nature of mobility data, educated and reasonable assumptions can be made about human behavior to attain the benefits of mobility data, as other studies have done in an effort to obtain generalized but large-scale observations in social science (Grantz et al., 2021; Monz et al., 2019). For this study, mobility data was advantageous in revealing insights where user demographic data was not collected or otherwise available, and it was a more uniform process than physically collecting demographic and occupancy data at every site in LA County. Such benefits could not be reasonably assessed without assumptions in interpreting mobility data. **In the future, it may be worthwhile to quantitatively assess the accuracy of this proxy metric. This may entail randomly sampling mobility data, particularly from center users who are unhoused, to see how the data accuracy responds.** Mobility data findings can also be paired with qualitative observations, surveys, and head counts at facilities for accuracy comparison.

Chapter 4. Transportation Analysis

Accessibility of cooling centers is an important factor to consider in examining cooling center use during extreme heat events. Proximity to public transportation and distances between the cooling centers and the users' home locations can affect whether the users visit a cooling center during extreme heat events. In this chapter, we examine the relationship between proximity to public transit stops and cooling center use, and how far users travel to get to cooling centers.

Public transportation can bolster access from residential areas to public areas in the urban environment that may otherwise be difficult to reach by walking, including formal and informal cooling centers. Berisha et al. (2017) found that 23% of the cooling center users in Maricopa County, Arizona traveled to cooling centers by public transportation. However, because public transportation systems tend to serve general areas of communities and urban areas, as opposed to specific communities and destinations, their effectiveness can be limited in improving cooling center accessibility during extreme heat events. Long walking distances between a transit stop and the location of a destination cooling center require a physical demand to access cooling centers, which during extreme heat events, puts individuals *en route* to cooling centers at an increased risk of heat-related illnesses (Nayak et al., 2019). Additional aspects that can further discourage individuals from public transportation utilization include a lack of shading infrastructure at transit stops, high fares, long wait times, and multiple transfers (Dzyuban et al., 2022, Nayak et al., 2019). For communities that do not have access to cooling systems at their places of residence, public transportation inaccessibility is especially a barrier to using cooling centers, as individuals of such communities also tend to not have reliable access to private transportation (Velaga et al., 2012).

In LA County, most cities maintain and govern their transit authority, and many urban areas are served by Metro, both of which connect residents of urban areas to common public places. However, rural areas, such as communities in the Antelope Valley, do not have widespread public transportation that is served by common transit authorities (Chu et al., 2021). For these underserved areas, a lack of sufficient public transportation can make it difficult for users to access a cooling center. In socio-economically disadvantaged areas of LA County, many public transportation stops that are accessible from homes do not adequately reach cooling centers. A study on distances between public transportation stops and formal LA County cooling centers found that in Supervisorial Districts 4 and 5 of LA County, which include areas such as South Bay, Catalina Island, Palmdale, and Lancaster, over 80% of the population lived outside of areas that could feasibly access cooling centers via public transportation. Additionally, over 90% of the population lived outside of areas that could access cooling centers via walking. A majority of these individuals were over 65 years of age and in poverty (Chu et al., 2021). Similarly, formal cooling centers in LA County tended to be located in areas with a high density of informal cooling centers, and less so in rural communities and areas of low socio-economic status (Fraser et al., 2018). Not only are LA County's formal cooling centers placed in areas that can be better served by informal cooling centers, but existing public transportation does not adequately support vulnerable groups in reaching cooling centers. Thus, both public transportation stops and formal cooling center placement can be strategically improved to enhance accessibility to cool spaces during extreme heat events.

Existing studies have closely examined the limitations of cooling centers and public transportation in LA County (Berisha et al., 2017; Chu et al., 2021). However, our understanding of spatial accessibility of cooling centers via public transportation and walking can be augmented with an analysis of actual users of cooling centers to further assess the efficacy of transit stop and cooling center placement in making cooling centers accessible. Mobility data, as demonstrated in the previous section of this report, can be used to roughly identify the characteristics of users of cooling centers, which can ultimately provide insight on distances between cooling center users' homes and the cooling centers that they use, as well as cooling center use. By using big data on mobile phone users in cooling centers, we can obtain a more comprehensive outlook on cooling center users throughout LA County than data that are obtained on users through surveys (Chu et al., 2021). This section of our study aims to expand on the existing scope of literature by analyzing information on cooling center users from mobility data in conjunction with spatial variables of cooling centers and public transportation stops.

We address our efforts to two key research questions:

- Can mobility data be used to detect an influence of proximity to public transportation on formal and informal cooling center use? If so, what is that effect?
- How far are users traveling to use cooling centers? How many users are within a walkable distance to a cooling center?

Methods

For our transportation analysis, we examined public transportation access and walkability of cooling centers. This section discusses the process of assessing the relationship between the distance of a cooling center to its nearest transit stop and the center's use. Additionally, this section explains our steps to calculating the distance users traveled to reach their cooling center.

Public Transportation

To assess cooling center accessibility and use within LA County, distances between cooling centers and public transportation stops were compared to the number of pings in cooling centers. A complete list of coordinates of transit stops was compiled from data provided by 23 major transit systems in LA County, including rail systems and buses. They were manually sorted to match 2017 transit stop records. Layers of the transit stops and the cooling center point layers were then loaded onto ArcGIS Pro and reprojected to the WGS 1984 Universal Transverse Mercator (UTM) 11N map projection system to ensure calculations were performed in meters. With the reprojected layers, the *Near Analysis* tool was used to calculate the Euclidean distance between cooling center point locations and the nearest transit stop, yielding a distance value in meters for every cooling center. Use was calculated for each cooling center by tallying the number of pings in a center during the entire study period. This procedure was done by matching the center FID and summing counts for each center in order to join counts of pings to the center polygon file. Distances were then compared with a scatterplot of distance to nearest transit stop and number of pings, a logarithmic scale, and a line of best fit. Data were separated by formal county, formal non-county, and informal cooling center types.

Distance to Home

This component of our analysis focuses on how far users traveled to reach the cooling center they used during hot and baseline days. The first step of the process was to aggregate the CSV files for hot days and baseline days. The CSV files contained the latitude and longitude data for the user's resting location and the unique ID and location of the cooling center they visited. After aggregating the files, we had 18 CSVs in total, one for each cooling center type for both hot and baseline days. Using ArcGIS, the information in the CSV files was joined to the polygon layers using the unique ID that corresponds to each cooling center polygon, and the polygon layers contain the coordinates of the corresponding cooling center point location. After the join, we used the *XY to Line* tool in ArcGIS to create geodetic line features between each user's resting location and the visited cooling center. Once the lines were created, a field for distance was added to the attribute table. The *Calculate Geometry* tool was used to calculate the length of the geodetic lines in meters using the projection WGS 1984 UTM 11N. The new distance information was then exported to CSV format.

Results

In the following section, we present a deeper examination of our distance analysis and outline the trends present in visitor behavior related to public transportation and distance to home.

Public Transportation

To present the trend more clearly, the cooling centers with an outlier distance of more than 1,250 meters away from a public transportation stop were removed from the scatterplots (Table 10). 1,250 meters is more than triple the most commonly used acceptable walking distance of 0.25 miles (about 402 meters) used in research studies in the U.S. (Yang & Diez-Roux, 2012).

Table 10. Cooling Centers Greater Than 1,250 Meters Away from Public Transit Stops

	Center Name	Distance to Transportation Stop (meters)	Baseline Count	Hot Count
Formal County	Avalon Library	40,472	2	0
	Acton Agua Dulce Library	10,508	0	1
	Gen. Wm. J. Fox Airfield	3,592	0	0
	Pathfinder Park	2,503	1	2
Formal Non-County	Acton Park	12,456	0	0
	LA County Library - Topanga Library	5,771	3	1
	Los Angeles Public Library - Porter Ranch Branch	2,206	4	7
	Dexter Park	1,827	0	0
	Glendale Public Library - Brand Library aArt Center	1,516	0	0
	Glendale Public Library - Chevy Chase	1,414	0	0

	Branch Library			
	LA County Library - Agoura Hills Library	1,264	2	5
Informal	Santiago Square Shopping Center	8,836	5	6
	Apollo Community Regional Park	3,487	0	1
	YMCA North Valley Family Porter Ranch	2,222	25	24
	Porter Ranch Town Center Shopping Center	2,213	138	116
	Griffith Park Boys Camp	1,321	1	1

Despite being far away from public transportation stops, some outlier centers had high counts of visits recorded. The visitors might be the employees of these cooling centers. Some visitors could also visit the center by walking, driving, or other means of transportation, where the distance to public transportation would not matter too much. One of the outlier formal cooling centers, Avalon Library, is 40.4 km away from the nearest public transportation stop. This is because Avalon Library is located on Catalina Island, which we did not account for in the public transit systems included in our project.

Importantly, for informal cooling centers, the number of visits was largely driven by visits to shopping centers. Moreover, as analyzed in Chapter 2, the informal cooling centers tended to have visitors from all different social vulnerability tracts. This had important implications for the results in this chapter. For commercial shopping centers, accessibility to public transportation may not be a determining factor of whether users of low or moderate vulnerability tracts would visit or not. However, since users from high vulnerability tracts may lack access to a personal vehicle, poor public transportation access may hinder cooling center utilization.

The cooling center usage compared to the center's distance to the nearest public transportation stop were plotted (Figures 16, 17, and 18). The centers are aggregated into the broader categories of formal county, formal non-county, and informal centers for comparison. For all three figures, the maximum distances on the x-axis are standardized to 1,250 meters for more direct visual comparisons across the center types. Because of the clustered scatters, the number of visits is log-transformed on the y-axis for a clearer representation of the overall trend. The number of visits is added by one before log transformation so the centers with zero visits are included on the plot. If the curve has a steeper trendline and reaches zero at a smaller distance, it suggests that more users visit the centers that are closer to public transportation stops. All the trend lines have relatively low R^2 values of lower than 0.1, which is expected since we are measuring human behaviors, but general trends in relationships could still be observed.

For all three cooling center categories, there is a similar behavior between baseline and hot days: as the distance to the nearest public transportation stop increases, the number of visits decreases. The hot day trend lines seem to have a steeper gradient across all three broader center types, which suggests that on hot days, the cooling centers further away from public transportation stops were less frequently visited. The informal cooling center trend lines reach zero at the furthest distance. The formal county and non-county cooling center trend line reaches zero at around 1,000 meters away from the nearest transportation stop. This suggests the accessibility of cooling centers by public transportation could affect the usage of cooling centers.

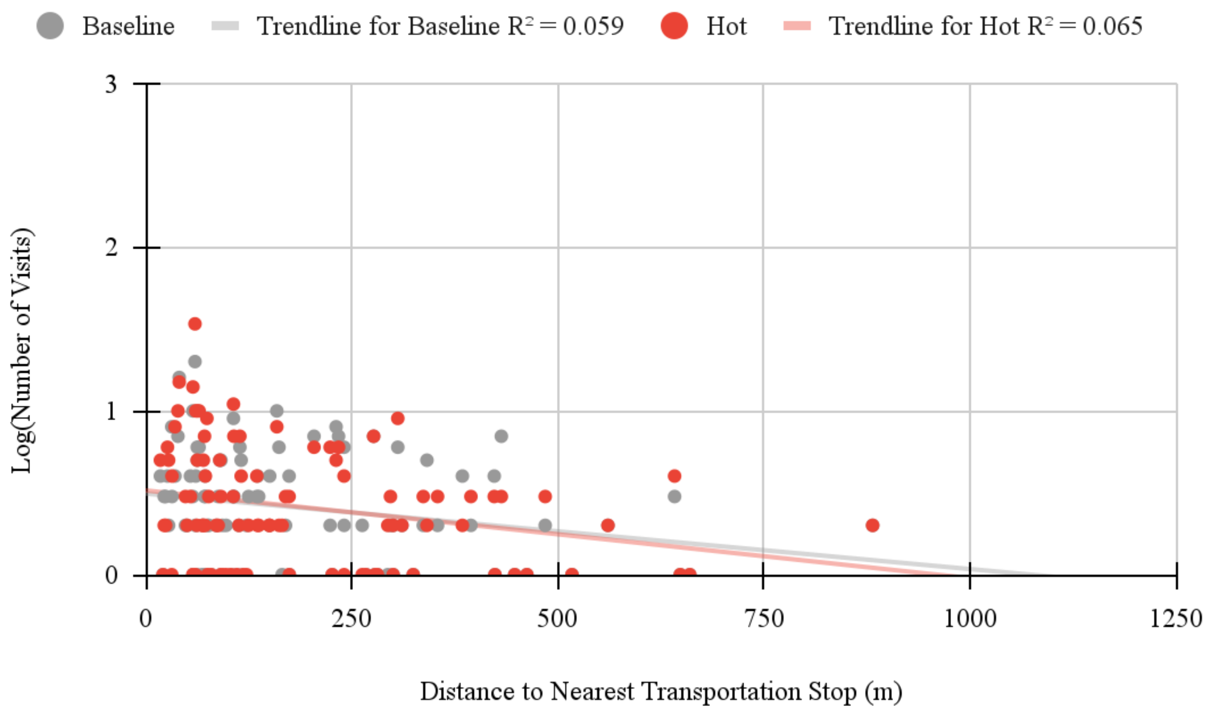


Figure 16. Formal County Cooling Center Usage vs. Distance to Nearest Transit Stop

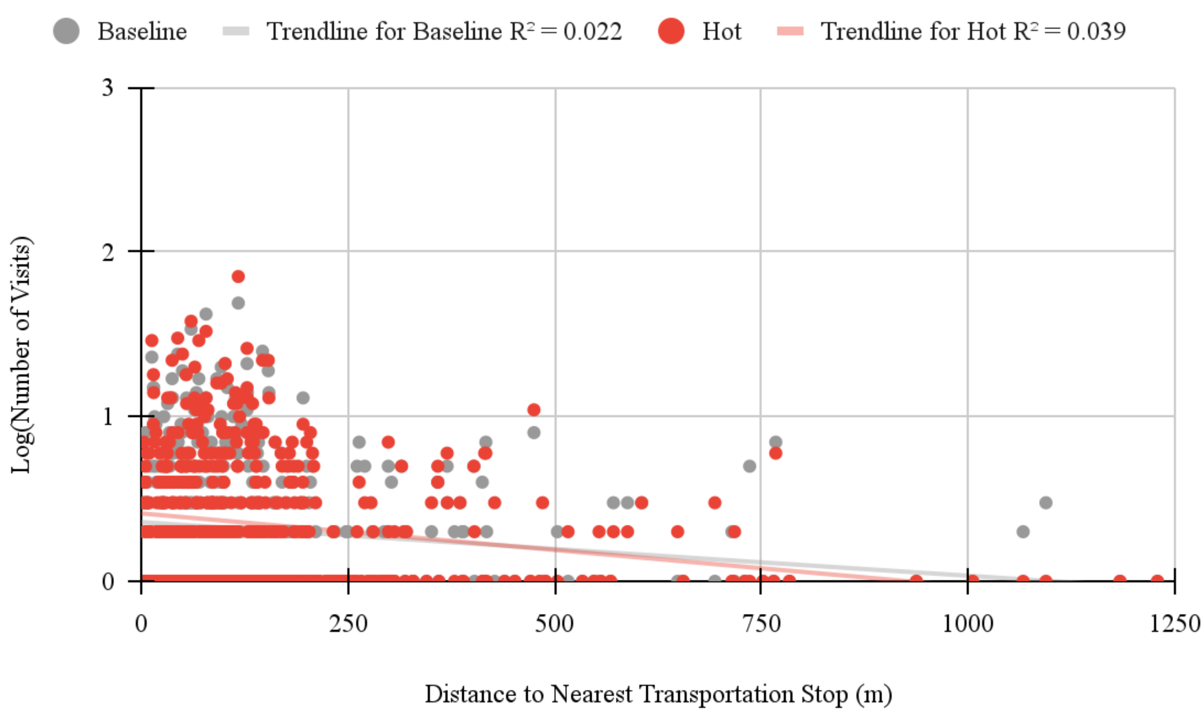


Figure 17. Formal Non-County Cooling Center Usage vs. Distance to Nearest Transit Stop

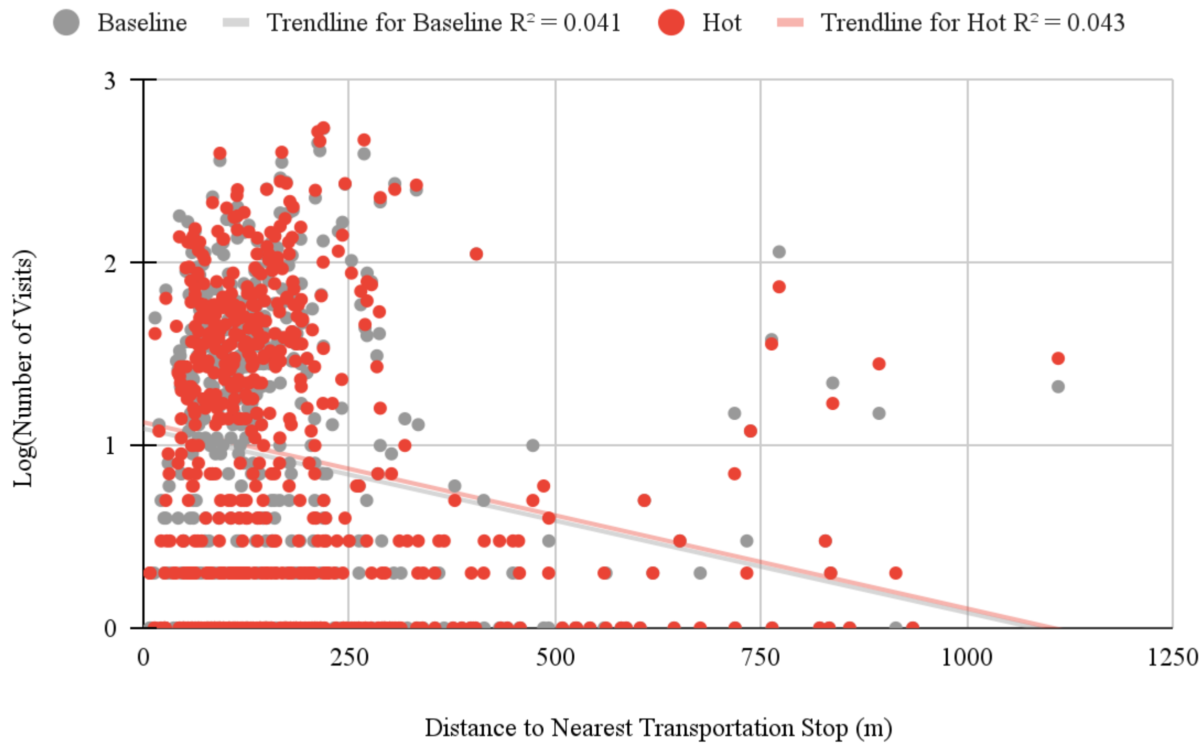


Figure 18. Informal Cooling Center Usage vs. Distance to Nearest Transportation Stop

In relation to our Chapter 2 analysis, we want to further investigate if this observed relationship will change for centers located in tracts with different SSI levels. After separating the formal and informal centers based on their SSI level of low, moderate, and high sensitivity, we use similar parameters and log transformation as in calculating cooling center users to average distance to transit stops (Figures 16 to 18) to create the figures plotting cooling centers in SSI tracts (Figures 19 to 27).

In all centers, regardless of the SSI level, a similar trend is observed as the number of visits decreases as the distance to the nearest transportation stop increases for both baseline and hot days. For formal county cooling centers, the moderate sensitivity trend lines reach zero at the shortest distance. This suggests that more users visit the formal county cooling centers closer to public transportation stops in moderate vulnerability tracts than the other tracts (Figures 19 to 21). For formal non-county cooling centers, as social sensitivity increases from low to high, the trend line reaches zero at a decreased distance, suggesting that more users in higher sensitivity tracts visit formal non-county cooling centers that are closer to public transit stops than the other tracts (Figures 22 to 24). For informal cooling centers, the high sensitivity trend lines reach zero at the shortest distance, suggesting that more users visit the informal cooling centers closer to public transportation stops at high vulnerability tracts than the other tracts (Figures 25 to 27). Therefore, though we cannot know if the users indeed visit the cooling centers by public transportation, this suggests that higher accessibility to public transportation could positively affect the usage of cooling centers, especially in areas with higher social sensitivity.

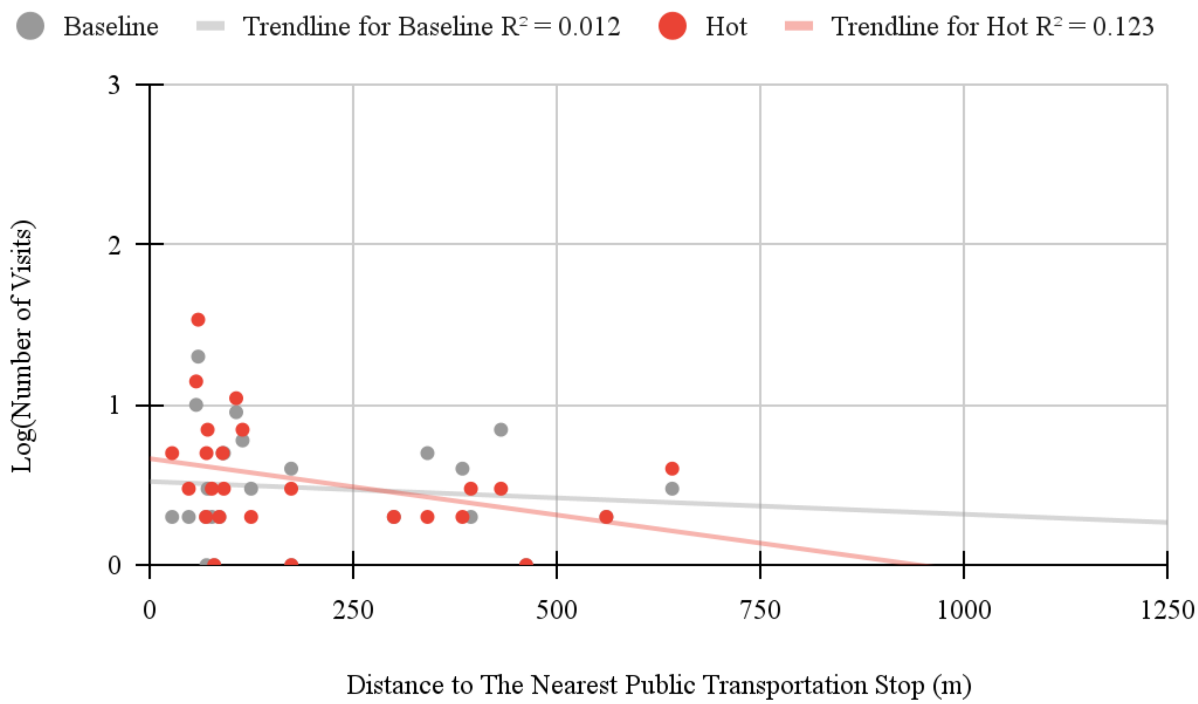


Figure 19. Formal County Cooling Centers in SSI Low Sensitivity Tracts

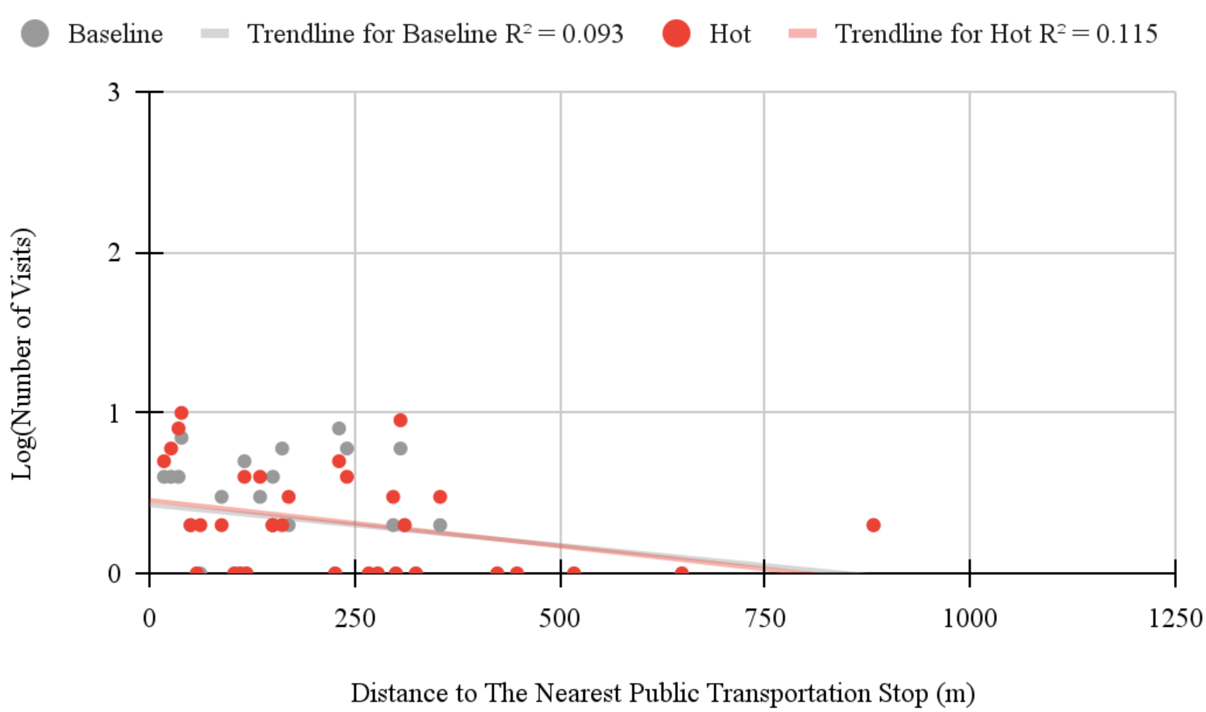


Figure 20. Formal County Cooling Centers in SSI Moderate Sensitivity Tracts

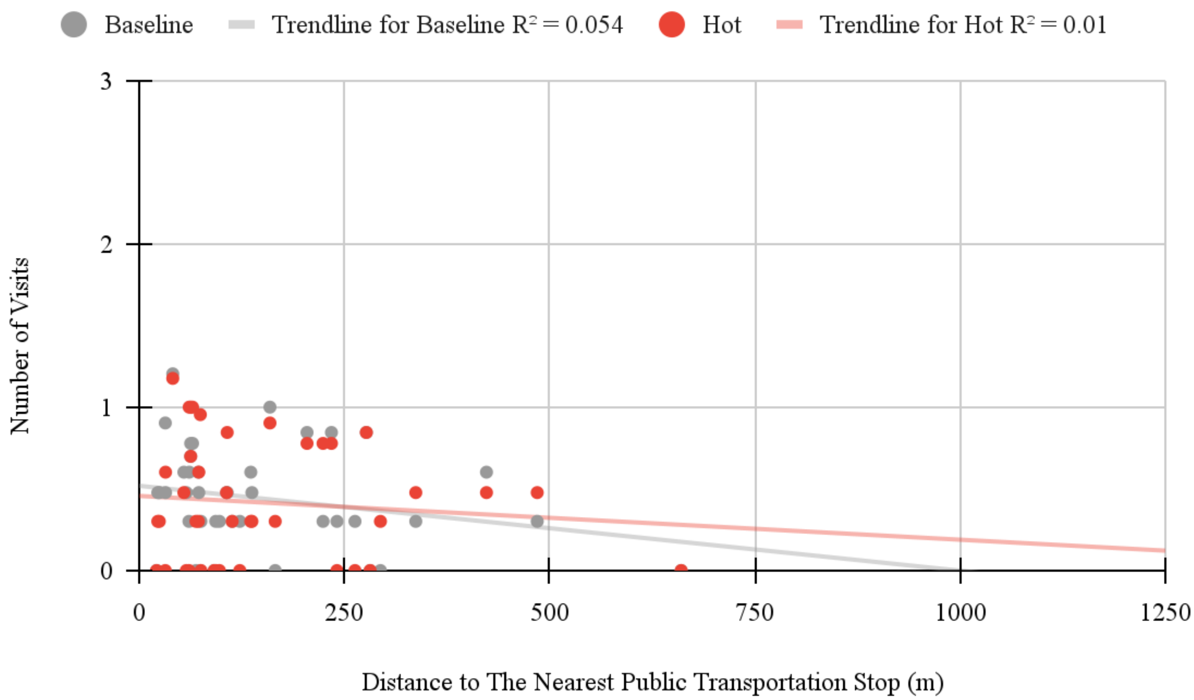


Figure 21. Formal County Cooling Centers in SSI High Sensitivity Tracts

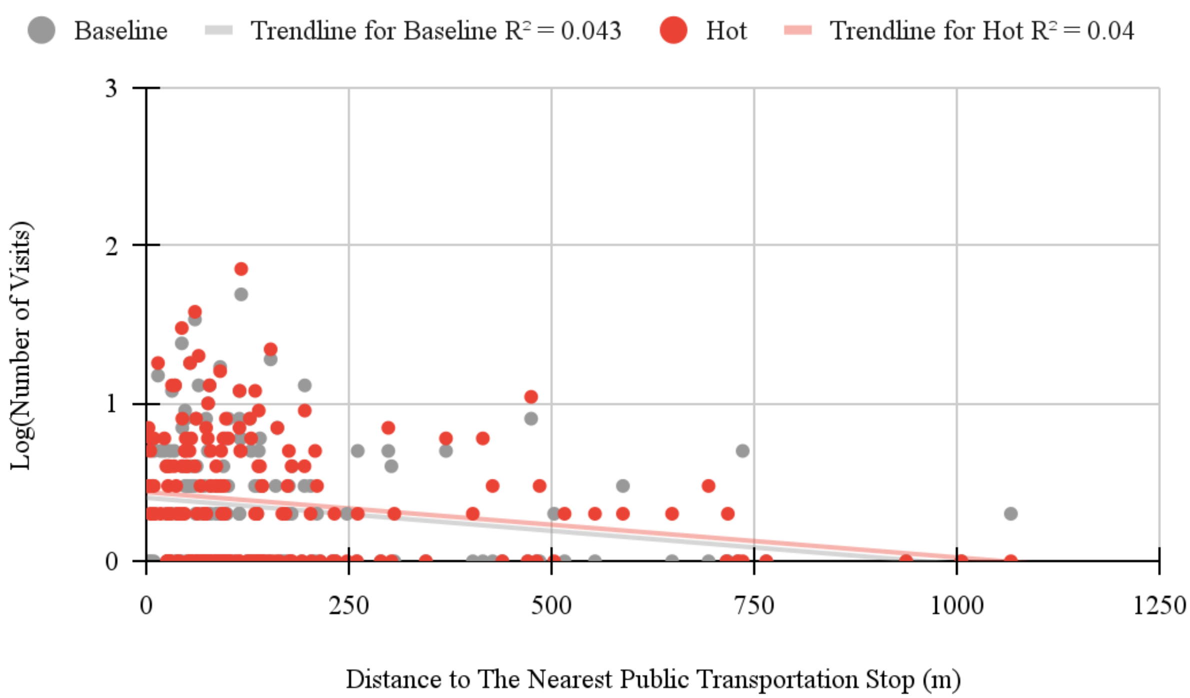


Figure 22. Formal Non-County Cooling Centers in SSI Low Tracts

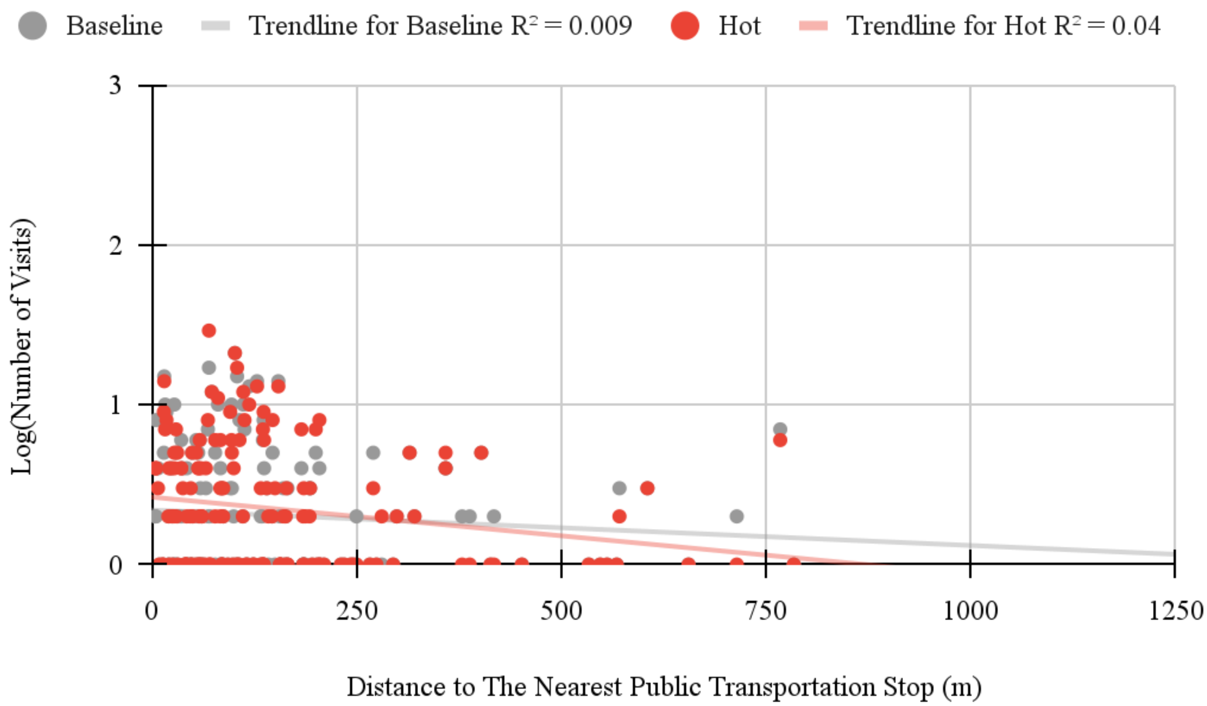


Figure 23. Formal Non-County Cooling Centers in SSI Moderate Tracts

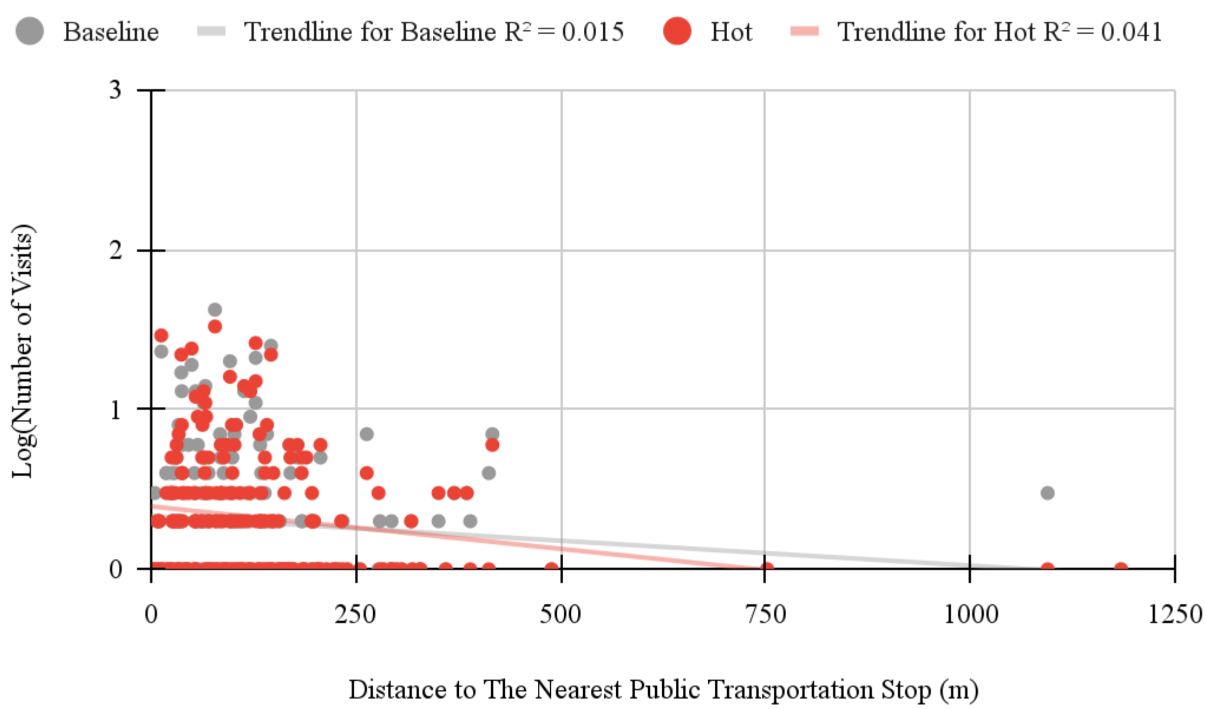


Figure 24. Formal Non-County Cooling Centers in SSI High Tracts

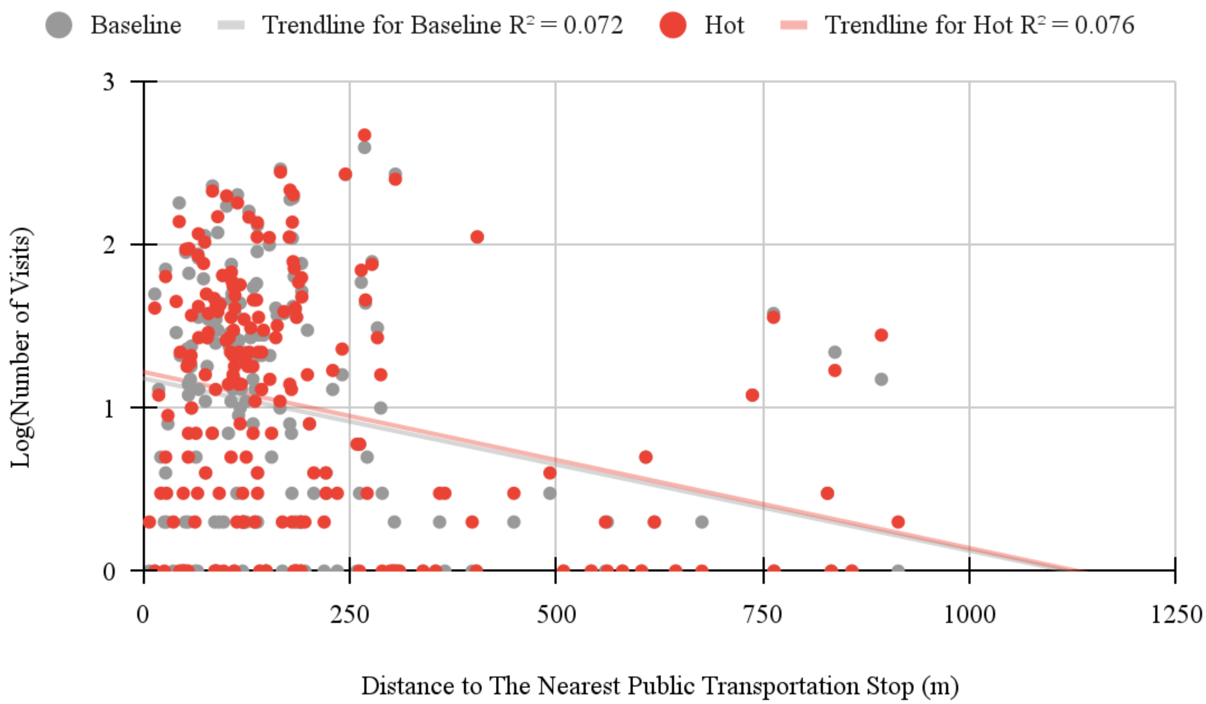


Figure 25. Informal Cooling Centers in SSI Low Tracts

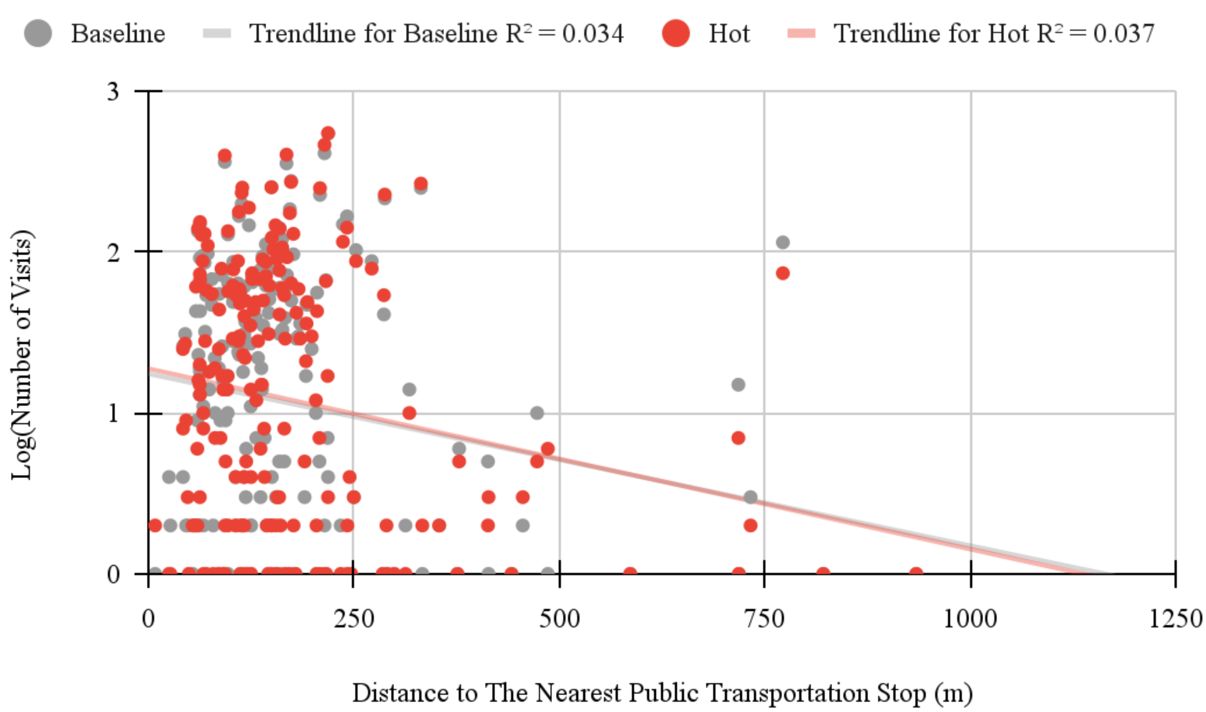


Figure 26. Informal Cooling Centers in SSI Moderate Tracts

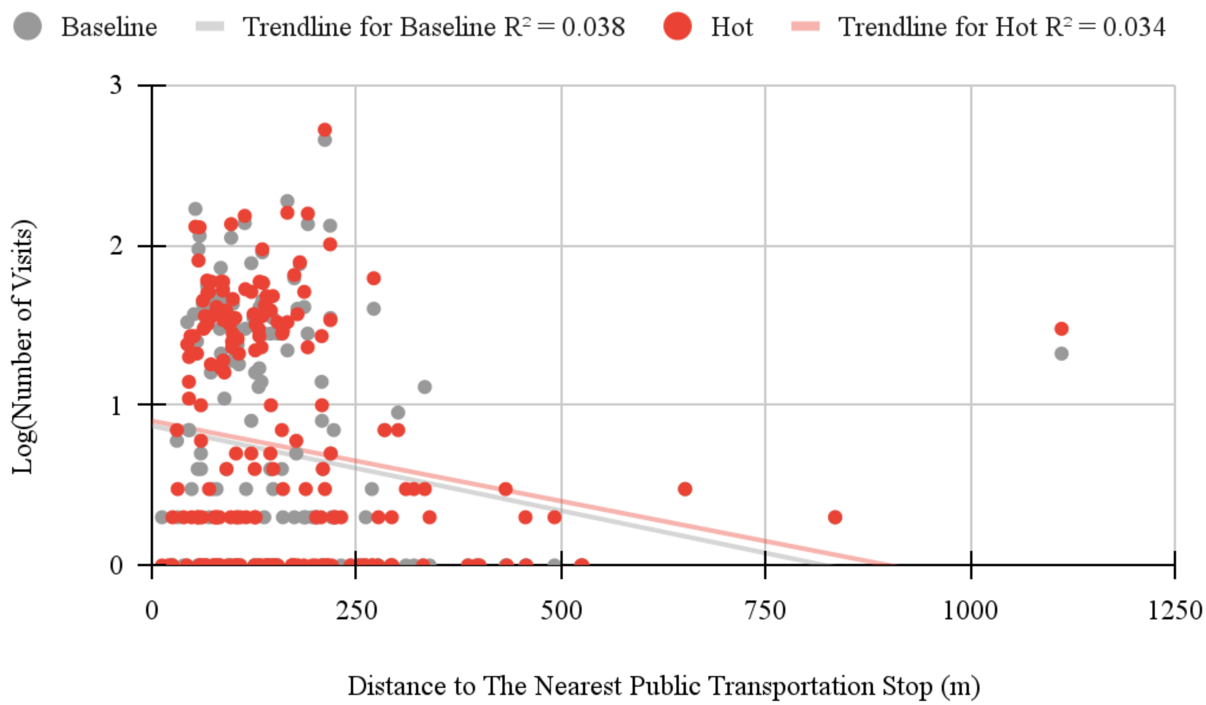


Figure 27. Informal Cooling Centers in SSI High Tracts

Lastly, the distances between cooling center point locations and the nearest public transportation stops are calculated in Euclidean distances, which did not take into account the road network. For future research, a more extensive closest facility analysis (Network Analyst tool) can be performed to further examine the relationship between proximity to public transportation and cooling center usage.

Distance to Home

To understand the population coverage and usage scale for different category types, we analyzed how the distance between the user's resting location and the cooling center visited varies among the cooling center categories. The unit of distance traveled by the users is converted to kilometers. The percentage of users in each two kilometer interval is calculated, and the users traveling more than 30 kilometers are aggregated. The maximum value on the vertical axis is set to be 30% for more direct visual comparisons across categories.

For baseline days, the informal centers showed the largest range of distance traveled, with a maximum of 88 km, followed by formal non-county with a maximum distance traveled of 80 km. Formal county centers had the smallest range of distance traveled with a maximum of 62 km. However, both informal and formal county centers showed the majority of users traveling between approximately 0 to 4 km, while formal non-county centers saw a majority of users traveling between 0 to 2 km (Figures 28 to 30). Thus, formal non-county centers may service more localized regions compared to formal county and informal centers as users are traveling both from shorter distances and more similar distances. The longer distance traveled to formal county centers in particular may be partly explained by the rural locations of some of these centers. Additionally, as informal centers are mainly commercial shopping centers, the draw of informal center users is likely widespread across the county.

The distributions of user distance traveled on hot days revealed subtle changes for all center types. First, while the maximum distance increased for both informal and formal county centers, this range decreased for formal non-county centers. This further supports how formal non-county centers service a more localized region, as users are traveling from an even smaller range of distances. For formal county centers, the number of users within 0 to 2 km notably increase on hot days, and the distribution becomes further skewed left; this shift may indicate that during heat events, formal county center visitors become more localized and travel shorter distances to these facilities. This shift may reflect how extreme heat drives more localized visitation of formal county and non-county centers.

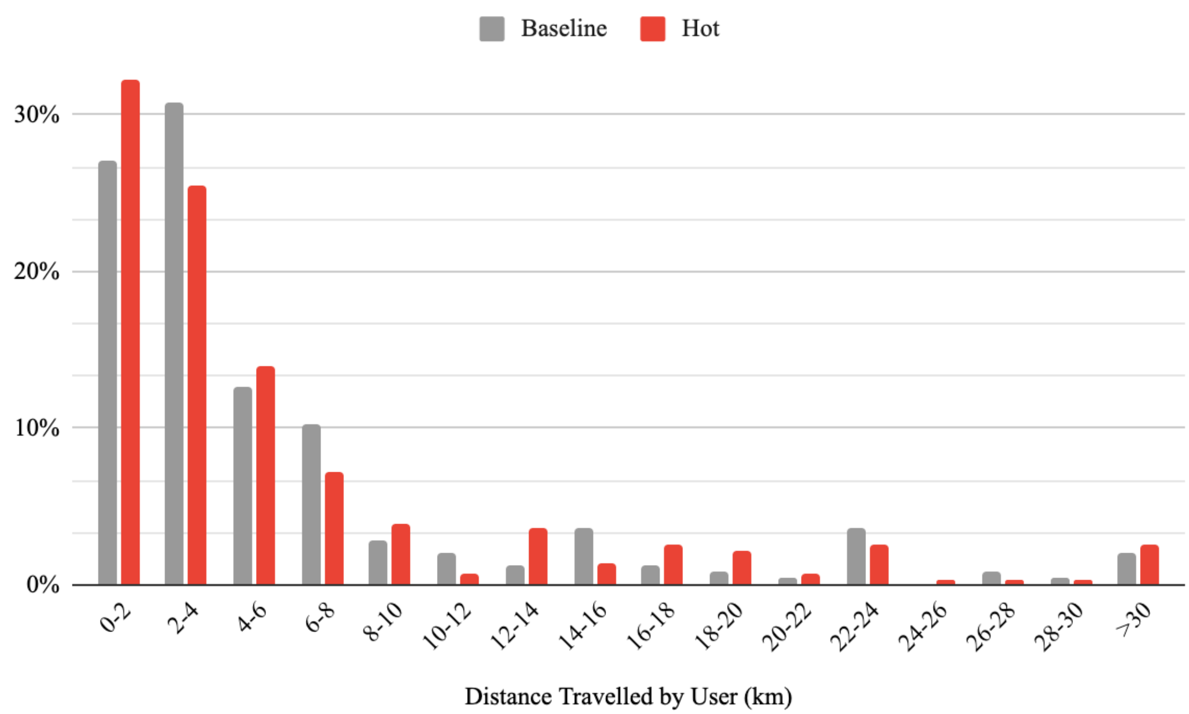


Figure 28. Percentage of Users vs. Distance Traveled for Formal County

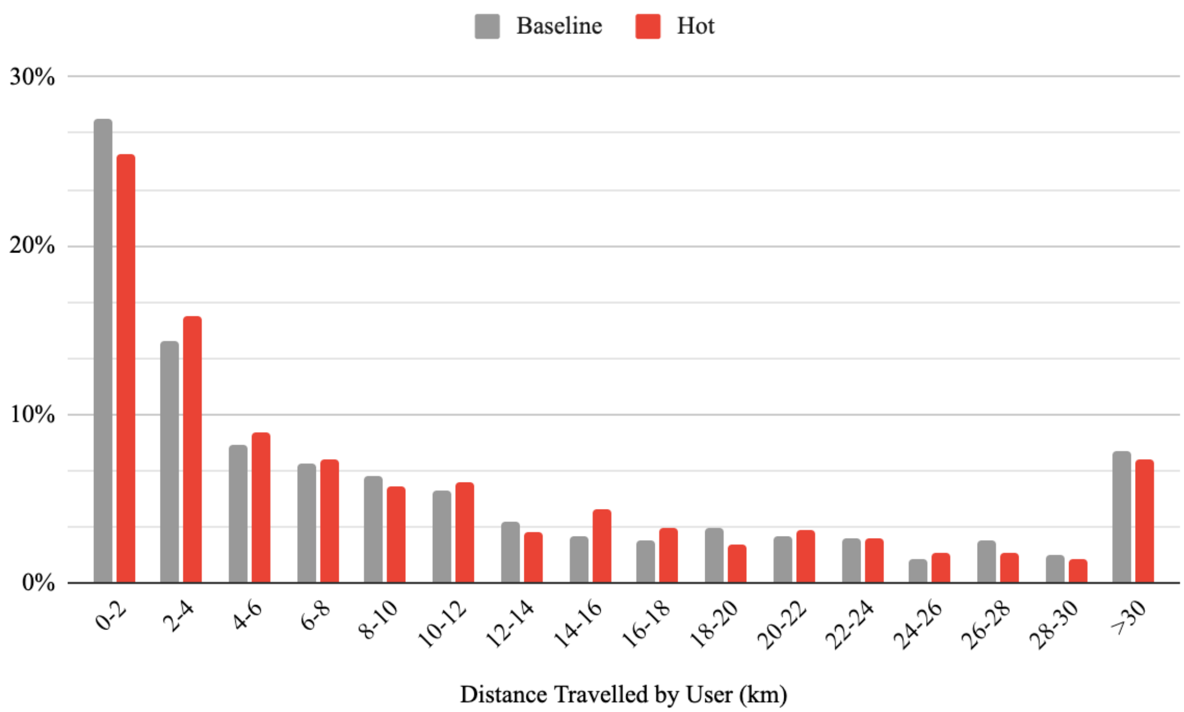


Figure 29. Percentage of Users vs. Distance Traveled for Formal Non-County

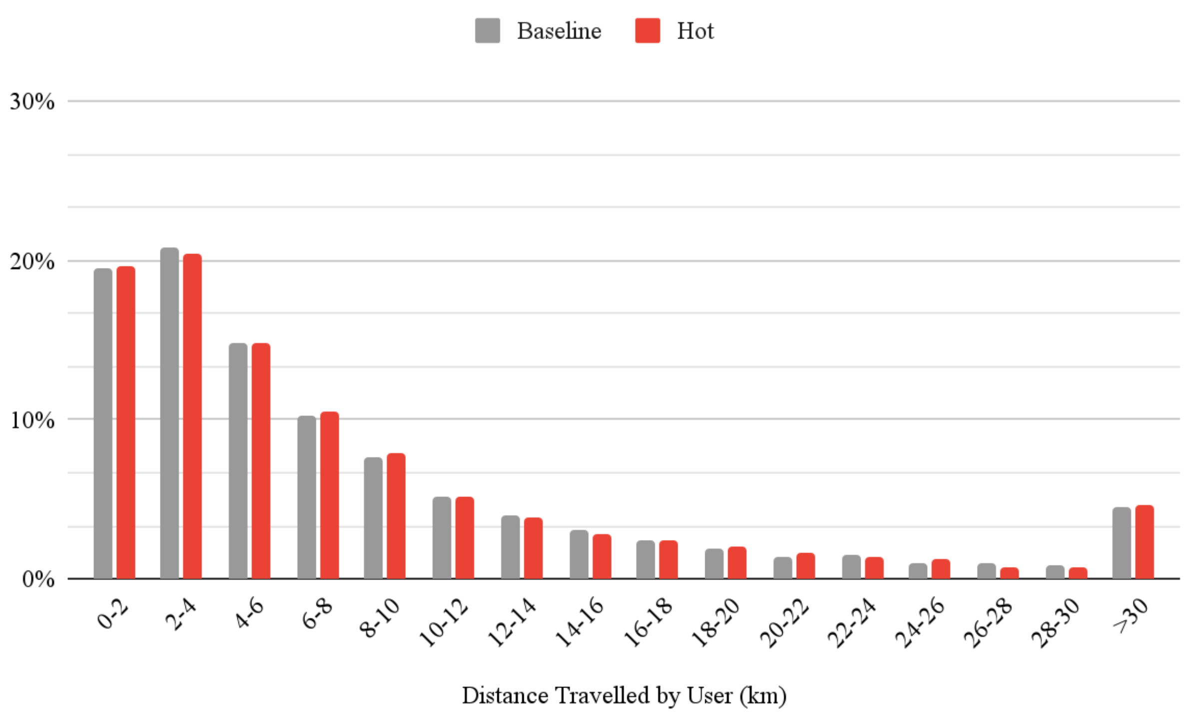


Figure 30. Percentage of Users vs. Distance Traveled for Informal

To further understand population coverage and regions of service, we investigated the proportion of user visits to cooling centers within a walkable distance to the user's home location. We used a radius of 0.25 miles as a walkable distance, a widely used metric in public health research in the United States (Yang & Diez-Roux, 2012). Formal non-county centers have the highest percentage of visits within the walkable distance for baseline days, followed by formal county centers, and then informal centers (Figure 31). While we cannot know if the users actually walked to the centers, the formal non-county centers again exhibit a more localized region of service in having a higher proportion of visitors that live nearby the centers. We found interesting variations for center visits between hot and baseline days. For all center types, the percentage of all visits that are within a walkable distance of 0.25 miles decreases for all centers from baseline days to heat days (Figure 32). Formal county centers saw a decrease of more than 50%. This may suggest that the walkability of a cooling center may not necessarily enhance the accessibility of a center during periods of extreme heat, as the heat may deter people from walking outside.

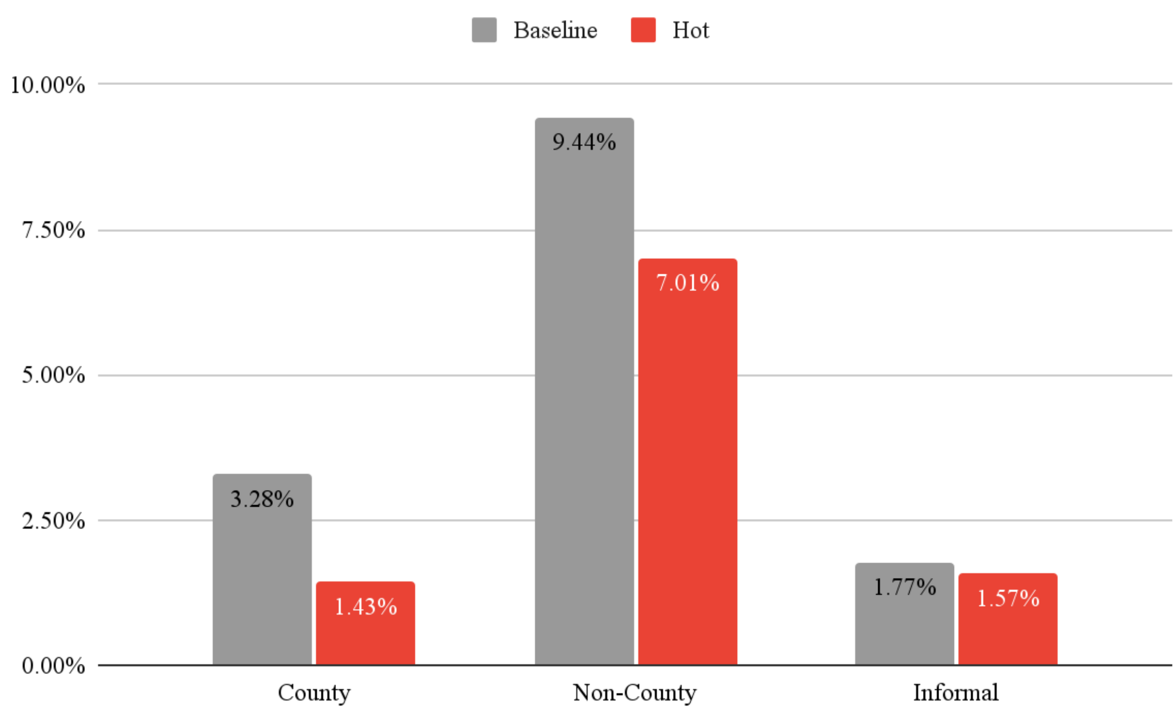


Figure 31. Percent of Visits Within Walkable Distance (0.25 miles)

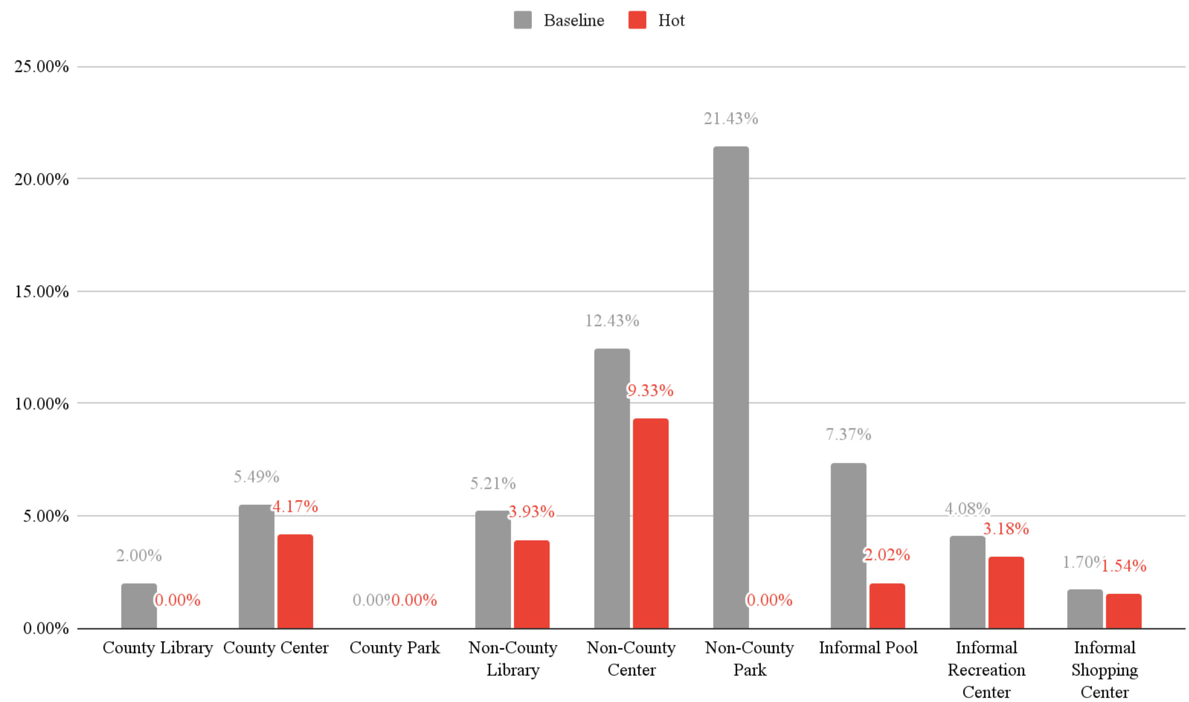


Figure 32. Percent of Visits Within Walkable Distance (0.25 miles) of all Center Types

To investigate how the vulnerability of cooling center users affects the distance users traveled to cooling centers, we further analyzed how the distance traveled to each of the category types varies with the SSI level of users' residence tracts. The distance users traveled for each cooling center category by SSI level for baseline and hot days was plotted (Figures 33 to 35). For informal centers (Figure 35), the median distance traveled showed a very slight increase for the users living in highest vulnerability tracts compared to users from moderate and low vulnerability tracts. Thus, the vulnerability of users' residence tracts does not appear to impact the distance users travel to informal centers. Formal county centers (Figure 33) showed a decrease in distance traveled as vulnerability level increased. The least vulnerable users of low SSI showed the largest decrease in the median distance traveled from baseline to hot days. While the median of high SSI, or the most vulnerable users, did not change between hot and baseline days, the downward shift of the box plot on hot days suggests that more users on hot days are traveling shorter distances; the median distance of users from the most vulnerable tracts was smaller than that of users from moderate and low vulnerability tracts. This discrepancy is further magnified for formal non-county centers (Figure 34), as the median for both hot and baseline days for users from the most vulnerable tracts is notedly shorter than that of users from moderate and low vulnerability tracts. For all vulnerability groups, the distance traveled did not show much variation between hot and baseline days for formal non-county centers. Thus, these results suggest that for county and non-county centers, users from high vulnerability tracts tend to travel shorter distances to visit these centers, which follows results from Question 2 that users from higher vulnerability tracts tend to visit more local formal cooling centers on hot days.

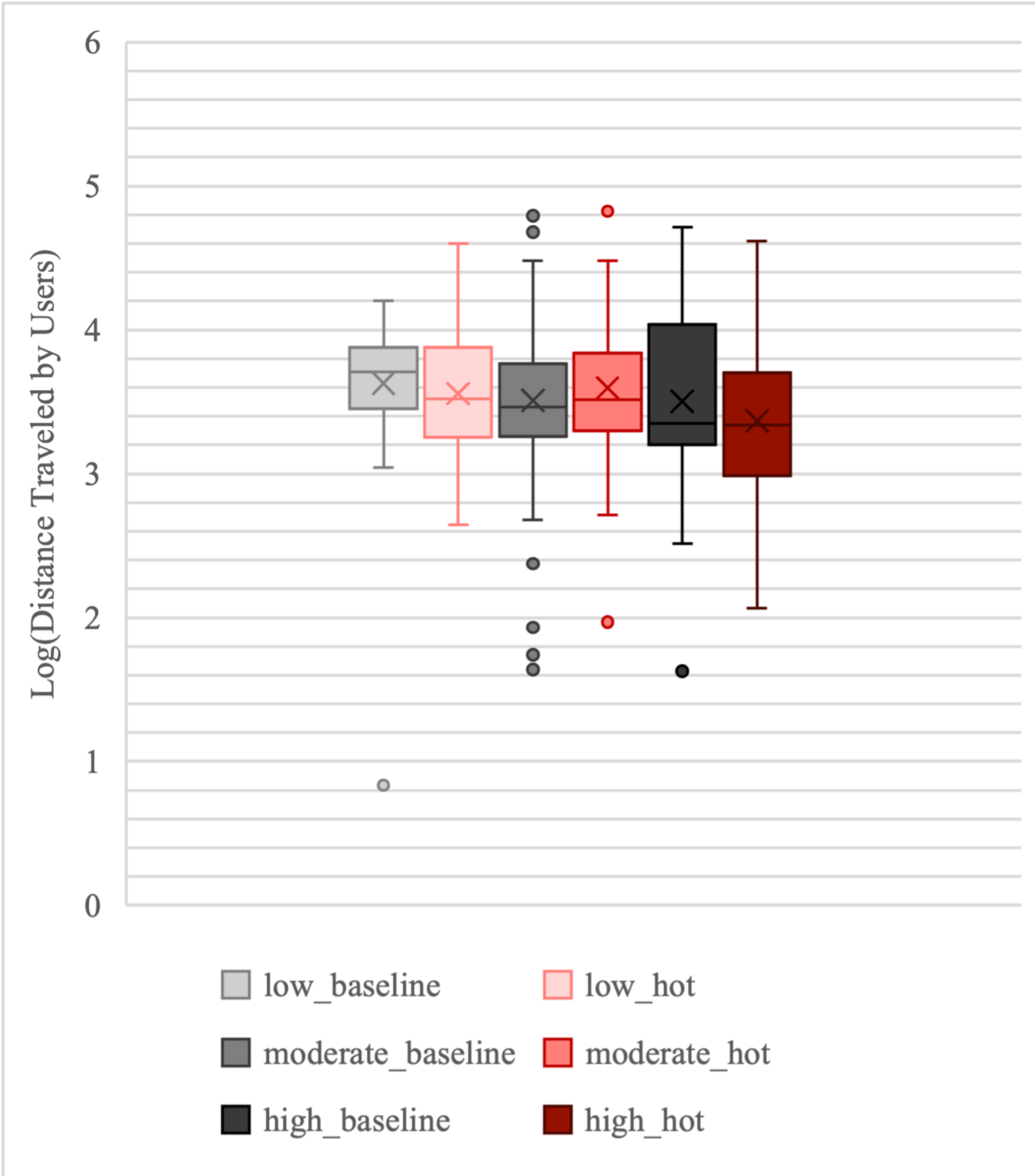


Figure 33. Formal County Cooling Centers: Distance Traveled by Users

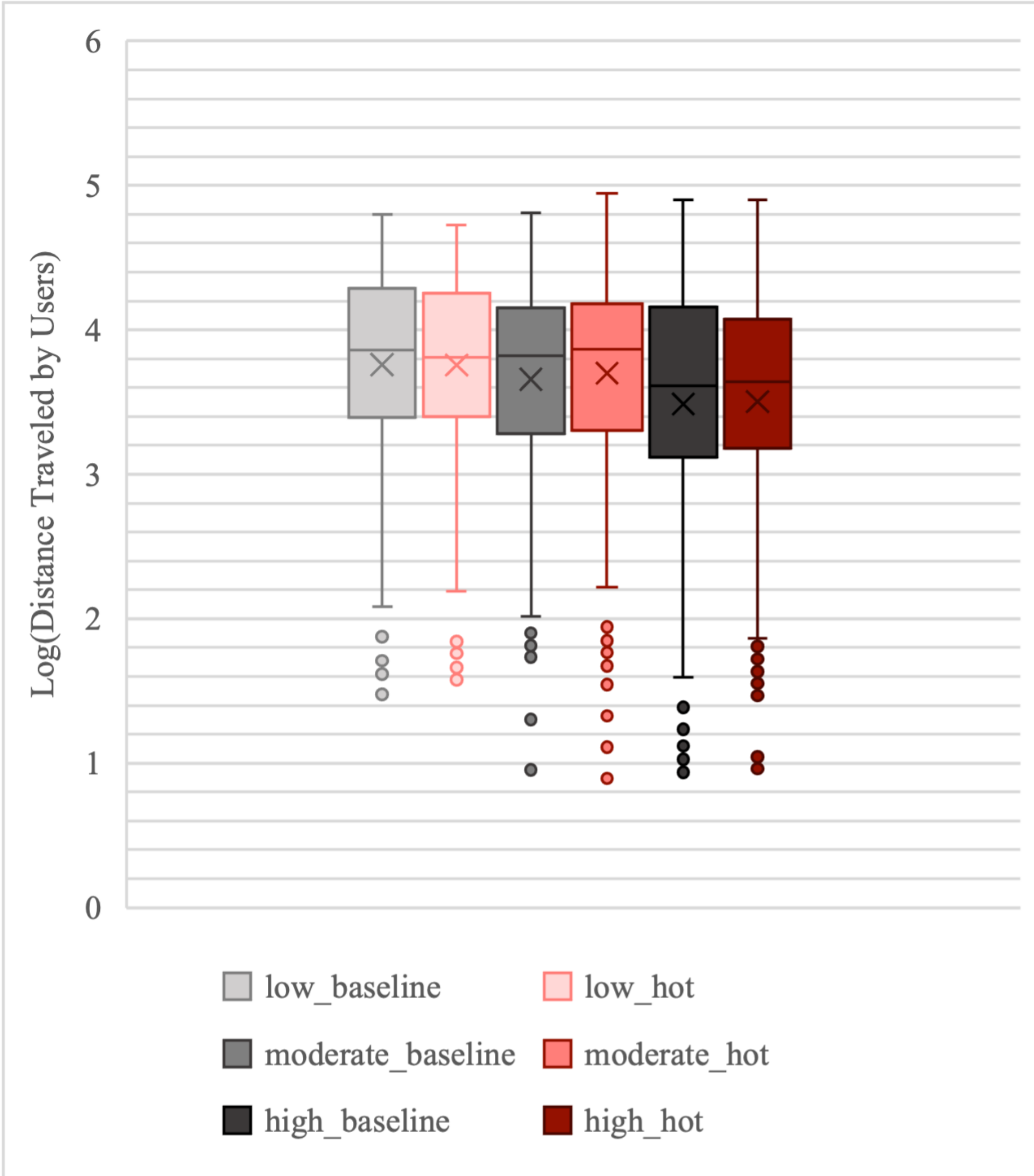


Figure 34. Formal Non-County Cooling Centers: Distance Traveled by Users

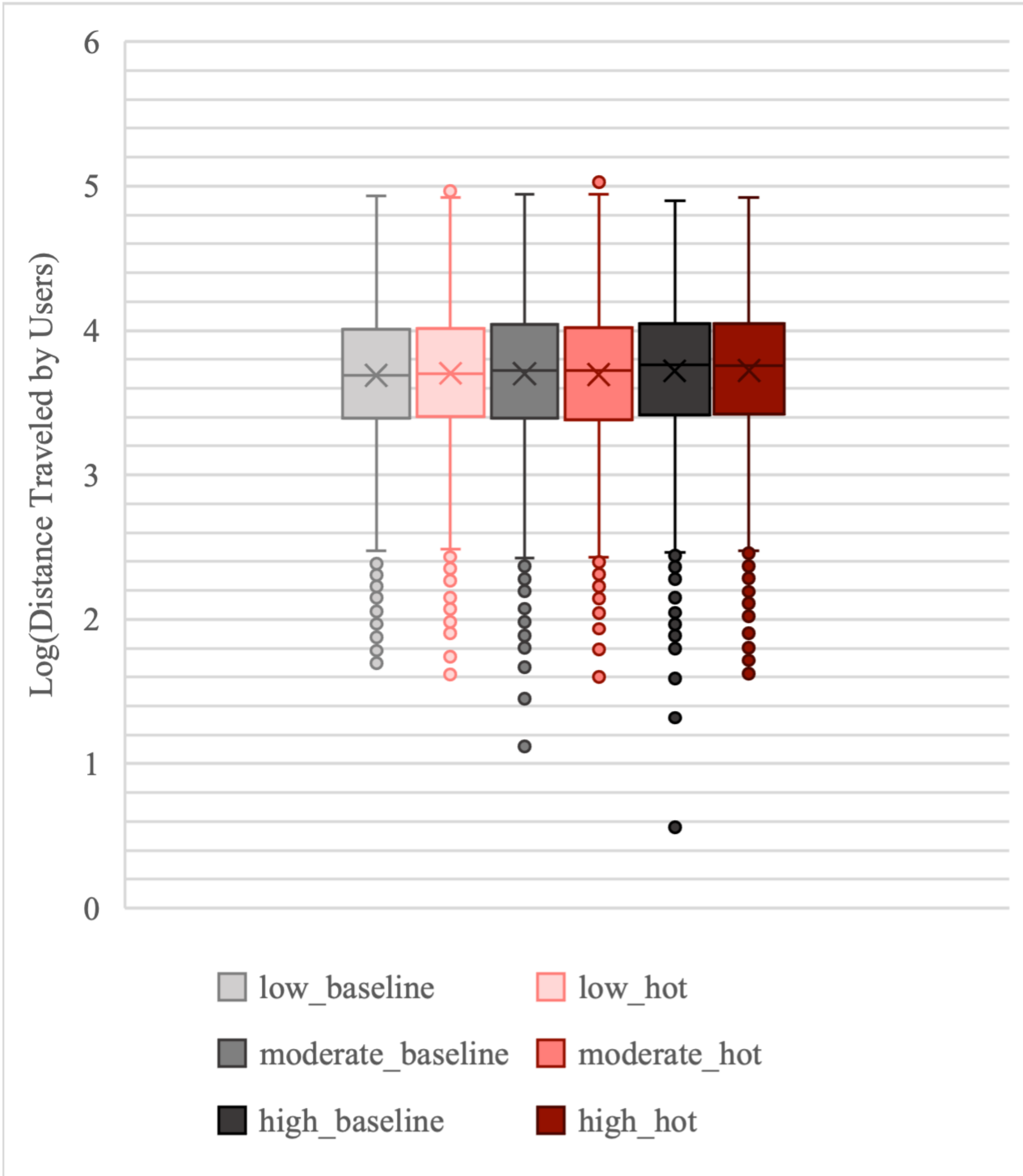


Figure 35. Informal Cooling Centers: Distance Traveled by Users

Discussion

Our analysis of public transportation access and distance traveled by user provides insight about the scale at which the cooling center types serve their community as well as how public transit enhances cooling center usage among different social vulnerability tracts.

Regardless of category, all cooling centers with shorter distances to public transit stops also saw higher visitation compared to those centers with farther distances to public transit stops. Therefore, though we cannot know if the users indeed visit the cooling centers by public transportation, this result suggests that **greater accessibility to public transportation could positively affect the usage of cooling centers, particularly in areas of higher social sensitivity**. Sampson et al. (2013) found through their survey of cooling center patrons that a quarter of the visitors traveled to a cooling center via public transport, which reinforces our result that access to public transit is both a crucial and advantageous resource to ensure cooling centers can serve all but especially those at higher risks of health complications from extreme heat.

The distributions of user distance traveled on hot days revealed subtle changes for all center types. We found that formal non-county centers show the smallest range of distances traveled, which may suggest that formal non-county centers service a more localized region, as users are traveling from a smaller range of distances. Extreme heat may also impact the community range cooling centers serve, as we found an overall decrease in distance traveled from baseline to hot days. This shift may reflect how extreme heat drives more localized visitation of formal county and non-county centers. Moreover, when looking at the user distance traveled by vulnerability tracts, we found that for for county and non-county centers, users from high vulnerability tracts tend to travel shorter distances to visit these centers, which reinforces our vulnerability analysis results that users from higher vulnerability tracts tend to visit more local formal cooling centers on hot days.

Extreme heat itself may hinder public transit use; studies have found that public transit use tends to decrease on hot days and may even pose a health risk to users due to potentially long wait times and lack of shading at transit stops (Dzyuban et al., 2022; Nissen et al., 2020). A study focused on public transportation in Qatar, a location with similar city characteristics to LA, yielded similar results (Shabban & Siam, 2021). Similarly, in our analysis of walkability and cooling center use, we found that usage of cooling centers within a walkable distance of user homes decreased on hot days compared to baseline days; this decrease may suggest that the walkability of a cooling center may not necessarily enhance the accessibility of a center during periods of extreme heat, as the heat may deter people from walking outside. Thus, the potential for heat exposure from public transit or walking may undermine the utility of these transportation methods, raising the importance for how cooling center accessibility can be enhanced without increasing people’s heat exposure and therefore risk of health complications during extreme heat events.

Chapter 5. Conclusion

Summary of Results

Although we did not find statistically meaningful differences in cooling center occupancy between hot and baseline days due to our limited sample size, the interesting variation in occupancy among center types between baseline and hot days may warrant further investigation of more sample days to compare to our results. Namely, the prolonged occupancy of all cooling centers on hot days compared to baseline days, specifically in the peak hours of heat in the afternoon, may suggest a more discriminate use of these centers for cooling purposes. We also found that formal non-county centers saw higher average occupancy for both hot and baseline days, followed by informal centers. Despite being the officially listed cooling resource available for the county, formal county centers showed the lowest usage of the cooling center categories. Moreover, while formal county centers and formal non-county libraries exhibited an increase in occupancy from baseline to hot days, formal county libraries showed an unexpected decrease in occupancy.

Mobility alone can show but not necessarily explain why formal county facilities showed lower occupancy, for example, or why formal county library occupancy decreased on hot days compared to baseline days. By including a case study of interviews to generate qualitative observations and information, we aimed to provide a more comprehensive framework to understand the spatial and behavioral phenomena underlying the trends of cooling center occupancy resulting from our mobility data analysis. While we were unable to conduct as many interviews as planned, the lack of cooling center awareness among facility employees contacted provided important context for cooling center usage in the county generally. That is, the limited knowledge and observations of cooling center operators may indicate larger issues related to advertisements of this resource that hinder more widespread adoption of cooling center use as a health-promoting behavior to combat extreme heat. The singular method of online advertisements via social media also introduces the issue of the digital divide and depriving those with limited internet access to vital health information and resources in the face of extreme heat and natural hazards generally.

Understanding the demographics of cooling center users across the county is key to addressing the uneven distribution of extreme heat impacts on people of different vulnerability groups. To do so, we analyzed the distribution and usage of cooling center types by low, moderate, and high levels of social sensitivity. We looked at both where the different categories of centers tend to be located as well as the vulnerability of the users themselves. We found that collectively, all cooling centers are randomly distributed around the county and there are thus no cooling center "deserts", or areas of the county not serviced by this infrastructure. The categories of centers, however, showed differences in the vulnerability of areas served. Formal centers service a greater proportion of high vulnerability areas, while informal centers show a more equal distribution of service among low, moderate, and high sensitivity areas. Formal centers may thus act as important resources for high vulnerability areas to mitigate the health impacts of extreme heat. When examining user characteristics, county facilities located specifically in high sensitivity tracts showed an increase in users from high vulnerability tracts visiting on hot days. Non-county facilities showed this same trend of increased visitation from users living in high vulnerability tracts on hot days regardless of the social sensitivity tract of a given center, which suggests that non-county facilities serve users from a more diverse or wider range of communities.

Our final portion of analysis investigated how public transportation access impacts cooling center usage as well as the area of service provided by the different center categories. We found that for both hot and baseline days, cooling centers with closer transit stops saw higher visitation than cooling centers with less accessible public transportation stops. Formal non-county cooling centers also showed that as the social sensitivity level of users' residence tracts increased, their visitation to centers with closer transportation stops also increased. Public transportation access thus appears to enhance cooling center usage. Beyond public transportation access, we saw that formal non-county centers served more localized users than formal county and informal centers, therefore on average, users of formal county and informal centers travel farther distances to visit these centers. An important gap of information missing from our mobility data is the mode of transportation; however, using a defined metric of walkability, we found that walkability of a center may detract from its use during periods of extreme heat. Thus, transportation specifically via car or air-conditioned transit may be of the most beneficial use for enhancing access to all cooling centers in the county.

Policy Recommendations

Based on the results of our analyses, we generated a set of recommendations to improve cooling center knowledge and accessibility to increase the use of cooling centers in LA County.

- **Expanding cooling center awareness by diversifying cooling center advertisement methods**. The case study of the San Fernando Valley/Pacoima region magnified the lacking awareness of cooling center status even among employees of these facilities. The limited advertisement of cooling centers via social media and the internet may create an important barrier to entry for vulnerable populations in particular. One method of advertisement could include signage on public transportation to not only provide an additional avenue of advertisement, but also reach populations that may be overlooked through digital advertisements.
- **Incorporating non-county cooling centers into city-level heat mitigation plans**. The more localized use of formal non-county centers on hot days suggests that people are cooling off at centers close to where they live. Involving cities within the County to potentially advertise or more closely manage the non-county centers within their boundaries may better match the community scale at which these facilities serve. Being heavily utilized not only by patrons of high social vulnerability but also in a variety of vulnerability tracts across the county, bolstering the presence of formal non-county centers with more direct management may also improve cooling center utilization and thus health-promoting behavior for those facing the greatest impacts from extreme heat.
- **Using public transportation access as a metric to identify future cooling centers and enhance occupancy.** The clear relationship between increased center use with closer public transit stops indicates how ease of public transportation access enhances cooling center usage on hot days, particularly for populations of high social sensitivity that are also at higher risk of health complications from extreme heat. We suggest that public transportation access be highly considered when evaluating current centers or identifying future centers for expansion of the County's formal network.

Implications and Challenges of Mobility Data

One of the core objectives of our project was to test the feasibility of our processes. While this report shows that mobile phone data can be used for climate-resilient research and policymaking, it is important to note the challenges and workarounds for future replicability. The first general obstacle of our project was obtaining and analyzing the data. Big data is defined as large volumes of information that are hard to process and examine in traditional ways (Baig et al., 2020). Technological advances such as artificial intelligence and machine learning have eased this challenge (Ali et al., 2016). The advancement of computing abilities combined with the large amounts of data being collected every day from devices and online platforms creates endless research opportunities. Acquiring this data, however, can be difficult in academic settings or for public good projects because of the expense. For corporations, mobility data is viewed as an investment. Conversely, nonprofit groups are less likely to have the resources for these types of projects.

The initial size of the mobile phone data received from Outlogic was 180 GB in parquet format and 335 GB in CSV format. Because of the size, use of storage in the Amazon Web Service Cloud was necessary (purchased with project grants for Dr. Longcore's research group). We narrowed our study to 12 days, decreasing the data to 59.8 GB in CSV format, which we stored in a Google Drive. One four-hour period could contain 600,000 to 1.7 million pings. The time it took to run our code was a significant barrier to collecting data. Research Questions 1 (occupancy) and 2 (vulnerability) each took about 30 hours of runtime, not including the time spent writing and testing the code. A future workaround to the long runtimes would be to outsource the projects to the Hoffman 2 Cluster, a centralized computer at UCLA that offers computational and storage capabilities for the campus community (IDRE, 2020). We ran all the code on personal laptops which have comparatively limited processor speeds.

After collecting the occupancy data, we were surprised by the seemingly low mobile ping counts. Even though the data only represents 2% of the LA County population, and an even smaller percentage visited a cooling center and yielded a mobile phone ping, the digital size of our data suggested that numerous cooling center users would be tracked. However, after reframing these numbers for population and sample size, they better reflected the number of cooling center users. We can extrapolate from our small numbers, yet it was obvious that mobile phone pings do not capture every user at cooling centers.

Multiple visualization programs were used to analyze the data. These included R-studio, Google Sheets, Excel, and Python, each with their own strengths and accessibility levels. Each group member had differing capabilities with these software programs. This was inconvenient when passing information between group members for different steps of the data processing. The difficulty only increased with how many different subsets of data there were (i.e., baseline vs. hot, county formal vs. non-county formal vs. informal, and the differing center types).

One of the biggest challenges of mobility data is its multivariate nature. Factors such as time of day, day of the week, cooling center hours of operation, and the day's proximity to holidays can all affect occupancy outcomes. With all these factors in mind, it is difficult to make concrete conclusions about occupancy as it relates to impacts from extreme heat. One solution to reducing variability is to analyze more days from the dataset. In an ideal world, we would compare occupancy and temperature for the entirety of the dataset. Overall, this variability created uncertainty in our discussions. A lack of available literature and general consensus on this research topic also meant that we could not cross-reference our conclusions with other studies.

One future avenue of research would be to create a model of occupancy to temperature. By processing all of the data, one could look at the comparison on a continuous scale, looking for patterns in occupancy as temperatures rise, a form of dose-response assessment. The more data examined, the more complete the conclusions would be. Another possible project would be to develop a front-end interface for the client, such as RS21's Project Vibe. These interfaces are useful if the client wants to explore the demographic data of cooling center users on a more surface level, without having to deal with the details of data processing.

Literature Cited

Ali, A., Qadir, J., Rasool, R.u. et al. (2016). Big data for development: applications and techniques. *Big Data Analytics* 1(2). https://doi.org/10.1186/s41044-016-0002-4

Baig, M. I., Shuib, L., & Yadegaridehkordi, E. (2020). Big data in education: a state of the art, limitations, and future research directions. *International Journal of Educational Technology in Higher Education,* 17(44). https://doi.org/10.1186/s41239-020-00223-0

Bartley, K. (2022). *What are Call Detail Records (CDRs)?* OnSIP. https://www.onsip.com/voip-resources/voip-fundamentals/what-are-call-detail-records-cdrs.

Berisha, V., Hondula, D., Roach, M., White, J. R., McKinney, B., Bentz, D., Mohamed, A., Uebelherr, J., & Goodin, K. (2017). Assessing adaptation strategies for extreme heat: A public health evaluation of cooling centers in Maricopa County, Arizona. *Weather, Climate, and Society*, 9(1), 71–80. https://doi.org/10.1175/WCAS-D-16-0033.1

Boutet, A. & Gambs, S. (2019). Inspect what your location history reveals about you: Raising user awareness on privacy threats associated with disclosing his location data. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, 2861–2864. Association for Computing Machinery. New York, NY. https://doi.org/10.1145/3357384.3357837

Casa, D. J., DeMartini, J. K., Bergeron, M. F., Csillan, D., Eichner, E. R., Lopez, R. M., & Yeargin, S. W. (2015). National athletic trainers' association position statement: Exertional heat illnesses. *Journal of Athletic Training*, 50(9), 986–1000. https://doi.org/10.4085/1062-6050-50.9.07

Centers for Disease Control (2016). Climate Change and Extreme Heat: What You Can Do to Prepare. Public-use data file and documentation. https://www.cdc.gov/climateandhealth/pubs/extreme-heat-guidebook.pdf. November 29, 2021.

Chief Sustainability Office, LA County Climate Vulnerability Assessment (2021). Los Angeles County. Retrieved March 10, 2022.

Chu, H., Adams, J., Li, J., & Goldmuntz, S. (2021). *Equity Focused Heat Adaptation Strategies for Los Angeles County.* UCLA Luskin Center for Innovation, Los Angeles County Office of Emergency Management. https://innovation.luskin.ucla.edu/wp-content/uploads/2021/06/Equity-Focused-Heat-Adaptation-Strategies-for-LA-County.pd

Cutter, S.L., Boruff, B.J. & Shirley, W.L. (2003). Social Vulnerability to Environmental Hazards. *Social Science Quarterly*, 84(2), 242-261. https://doi.org/10.1111/1540-6237.8402002

Dzyuban, Y., Hondula, D. M., Coseo, P. J., & Redman, C. L. (2022). Public Transit Infrastructure and Heat Perceptions in Hot and Dry Climates. *International Journal of Biometeorology*, 66(2), 345–356. https://doi.org/10.1007/s00484-021-02074-4

Ferrer, R., & Klein, W. M. (2015). Risk perceptions and health behavior. *Current*

Opinion in Psychology, 5, 85–89. https://doi.org/10.1016/j.copsyc.2015.03.012

Fraser, A. M., Chester, M. V., & Eisenman, D. (2018). Strategic locating of refuges for extreme heat events (or heat waves). *Urban Climate,* 25, 109–119. https://doi.org/10.1016/j.uclim.2018.04.009

Galperin, H., Bar, F., & Nguyen, H. (2021). The power divide: Mobile communication in Los Angeles' Skid Row. *Mobile Media and Communication*, 9(1), 30–50. https://doi.org/10.1177/2050157920932608

Grantz, K. H., Meredith, H. R., Cummings, D. A. T., Metcalf, C. J. E., Grenfell, B. T., Giles, J. R., Mehta, S., Solomon, S., Labrique, A., Kishore, N., Buckee, C. O., & Wesolowski, A. (2020). The use of mobile phone data to inform analysis of COVID-19 pandemic epidemiology. *Nature Communications*, 11(1), 4961. https://doi.org/10.1038/s41467-020-18190-5

Harlan, S. L., Declet-Barreto, J. H., Stefanov, W. L., & Petitti, D. B. (2013). Neighborhood effects on heat deaths: social and environmental predictors of vulnerability in Maricopa County, Arizona. *Environmental Health Perspectives,* 121(2), 197–204. https://doi.org/10.1289/ehp.1104625

Hatchett, B. J., Benmarhnia, T., Guirguis, K., VanderMolen, K., Gershunov, A., Kerwin, H., Khlystov, A., Lambrecht, K. M., & Samburova, V. (2021). Mobility data to aid assessment of human responses to extreme environmental conditions. *The Lancet Planetary Health*, 5(10), e665–e667. https://doi.org/10.1016/S2542-5196(21)00261-8

Holec, J., Šveda, M., Szatmári, D., Feranec, J., Bobáľová, H., Kopecká, M., & Šťastný, P. (2021). Heat risk assessment based on mobile phone data: Case study of Bratislava, Slovakia. *Natural Hazards*, 108(3), 3099–3120. https://doi.org/10.1007/s11069-021-04816-4

Huang, X., Lu, J., Gao, S., Wang, S., Liu, Z., & Wei, H. (2021). Staying at home is a privilege: Evidence from fine-grained mobile phone location data in the United States during the COVID-19 Pandemic. *Annals of the American Association of Geographers*, 112(1), 286–305. doi:10.1080/24694452.2021.1904819

Hulley, G. C., Dousset, B., & Kahn, B. H. (2020). Rising trends in heatwave metrics across Southern California. *Earth's Future*, 8(7), 678–686. https://doi.org/10.1029/2020EF001480

IPCC. (2021). Summary for Policymakers. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [Masson-Delmotte, V. et al (eds)], 8–10. Cambridge University Press.

Institute for Digital Research and Education (IDRE). (2020). System overview. Hoffman2 Documentation. Retrieved May 9, 2022, from https://www.hoffman2.idre.ucla.edu/About/System-overview.html

Kalkstein, A. J., Kalkstein, L. S., Vanos, J. K., Eisenman, D. P., & Grady Dixon, P. (2018). Heat/mortality sensitivities in Los Angeles during winter: A unique phenomenon in the United States. *Environmental Health: A Global Access Science Source,* 17(1), 1–12. https://doi.org/10.1186/s12940-018-0389-7

Kenny, G. P., Yardley, J., Brown, C., Sigal, R. J., & Jay, O. (2010). Heat stress in older individuals and patients with common chronic diseases. *Canadian Medical Association Journal*, 182(10), 1053–1060. https://doi.org/10.1503/cmaj.081050

Kim, K., Jung, J., Schollaert, C., & Spector, J. T. (2021). A comparative assessment of cooling center preparedness across twenty-five U.S. cities. *International Journal of Environmental Research and Public Health*, 18(9), 4801. https://doi.org/10.3390/ijerph18094801

Kuras, E. R., Hondula, D. M., & Brown-Saracino, J. (2015). Heterogeneity in individually experienced temperatures (IETs) within an urban neighborhood: insights from a new approach to measuring heat exposure. *International Journal of Biometeorology,* 59(10), 1363–1372. https://doi.org/10.1007/s00484-014-0946-x

Mitchell, B. C., & Chakraborty, J. (2015). Landscapes of thermal inequity: Disproportionate exposure to urban heat in the three largest US cities. *Environmental Research Letters,* 10(11), 115005. https://doi.org/10.1088/1748-9326/10/11/115005

Monz, C., Mitrovich, M., D'Antonio, A., & Sisneros-kidd, A. (2019). Using Mobile Device Data to Estimate Visitation in Parks and Protected Areas: An Example from the Nature Reserve of Orange County, California. *Journal of Park and Recreation Administration*, 37(4), 9899. https://doi.org/10.18666/JPRA-2019-9899

Nayak, S.G., Lin, S., Sheridan, S. et al. (2017). Surveying local health departments and county emergency management offices on cooling centers as a heat adaptation resource in New York State. *J Community Health* 42, 43–50. https://doi.org/10.1007/s10900-016-0224-4

Nayak, S. G., Shrestha, S., Sheridan, S. C., Hsu, W.-H., Muscatiello, N. A., Pantea, C. I., Ross, Z., Kinney, P. L., Zdeb, M., Hwang, S.-A. A., & Lin, S. (2019). Accessibility of cooling centers to heat-vulnerable populations in New York State. *Journal of Transport & Health,* 14, 100563. https://doi.org/10.1016/j.jth.2019.05.002

Nissen, K. M., Becker, N., Dähne, O., Rabe, M., Scheffler, J., Solle, M., & Ulbrich, U. (2020). How does weather affect the use of public transport in Berlin? *Environmental Research Letters*, 15(8), 085001. https://doi.org/10.1088/1748-9326/ab8ec3

Peng, Z., Wang, R., Liu, L., & Wu, H. (2020). Fine-Scale Dasymetric Population Mapping with Mobile Phone and Building Use Data Based on Grid Voronoi Method. *ISPRS International Journal of Geo-Information*, 9(6), 344. MDPI AG. Retrieved from http://dx.doi.org/10.3390/ijgi9060344

Phillips, A. M., Barboza, T., Vives, R., & Greene, S. (2021, October 7). Heat waves are far deadlier than we think. How California neglects this climate threat. Los Angeles Times. Retrieved February 1, 2022, from https://www.latimes.com/projects/california-extreme-heat-deaths-show-climate-change-risks/

Rambhatla, S., Zeighami, S., Shahabi, K., Shahabi, C., & Liu, Y. (2022). Toward Accurate Spatiotemporal COVID-19 Risk Scores Using High-Resolution Real-World Mobility Data. ACM Trans. *Spatial Algorithms Syst.*, 8(2). https://doi.org/10.1145/3481044

Reid, C. E., O'Neill, M. S., Gronlund, C. J., Brines, S. J., Brown, D. G., Diez-Roux, A. V., & Schwartz, J. (2009). Mapping community determinants of heat vulnerability. *Environmental Health Perspectives,* 117(11), 1730–1736. https://doi.org/10.1289/ehp.0900683

Rice, W. L., & Pan, B. (2021). Understanding changes in park visitation during the COVID-19 pandemic: A spatial application of big data. *Wellbeing, Space and Society*, 2, 100037. doi:10.1016/j.wss.2021.100037

Riley, K., Wilhalme, H., Delp, L., & Eisenman, D. P. (2018). Mortality and morbidity during extreme heat events and prevalence of outdoor work: An analysis of community-level data from Los Angeles County, California. *International Journal of Environmental Research and Public Health,* 15(4), 2–3. https://doi.org/10.3390/ijerph15040580

Sampson, N. R., Gronlund, C. J., Buxton, M. A., Catalano, L., White-Newsome, J. L., Conlon, K. C., O'Neill, M. S., McCormick, S., & Parker, E. A. (2013). Staying cool in a changing climate: Reaching vulnerable populations during heat events. *Global Environmental Change: Human and Policy Dimensions,* 23(2), 475–484. https://doi.org/10.1016/j.gloenvcha.2012.12.011

Shaaban, K., & Siam, A. (2021). Public Transportation Usage in a Hot Climate Developing Country. 14th International Scientific Conference on Sustainable. *Modern and Safe Transport*, 55, 394–400. https://doi.org/10.1016/j.trpro.2021.07.002

Sheridan S. C. (2007). A survey of public perception and response to heat warnings across four North American cities: an evaluation of municipal effectiveness. *International Journal of Biometeorology,* 52(1), 3–15. https://doi.org/10.1007/s00484-006-0052-9

US EPA. (2021, August). Heat Island Effect [Collections and Lists]. United States Environmental Protection Agency. https://www.epa.gov/heatislands

Velaga, N. R., Beecroft, M., Nelson, J. D., Corsar, D., & Edwards, P. (2012). Transport Poverty Meets the Digital Divide: Accessibility and Connectivity in Rural Communities. *Journal of Transport Geography*, 21, 102–112. https://doi.org/10.1016/j.jtrangeo.2011.12.005

Verhoef, M. J., & Casebeer, A. L. (1997). Broadening horizons: Integrating quantitative and qualitative research. *The Canadian Journal of Infectious Diseases*, 8(2), 65–66. https://doi.org/10.1155/1997/349145

Wang, S. & Lu, R. (2021). *Northeast San Fernando Valley: Community-Controlled Solutions Built On Decades of Organizing*.

https://greenlining.org/publications/2021/community-controlled-solution-tcc-case-study/

Wheeler, S. M., Abunnasr, Y., Dialesandro, J., Assaf, E., Agopian, S., & Gamberini, V. C. (2019). Mitigating urban heating in dryland cities: A literature review. *Journal of Planning Literature*, 34(4), 434–446. https://doi.org/10.1177/0885412219855779

Widerynski, S., Schramm, P., Conlon, K., Noe, R., Grossman, E., Hawkins, M., Nayak, S., Roach, M., & Hilts, A. (2017). *The Use of Cooling Centers to Prevent Heat-Related Illness: Summary of Evidence and Strategies for Implementation*. Centers for Disease Control and Prevention. https://doi.org/10.13140/RG.2.2.32267.59688

Woo, S., Yoon, S., Kim, J., Hwang, S. W., & Kweon, S. J. (2021). Optimal cooling shelter assignment during heat waves using real-time mobile-based floating population data. *Urban Climate,* 38, 100874. https://doi.org/10.1016/J.UCLIM.2021.100874

Yang, Y., & Diez-Roux, A. V. (2012). Walking distance by trip purpose and population subgroups. *American Journal of Preventive Medicine*, 43(1), 11–19. https://doi.org/10.1016/j.amepre.2012.03.015

Yang, J., Zhou, M., Ren, Z., Li, M., Wang, B., Liu, D. L., Ou, C.-Q., Yin, P., Sun, J., Tong, S., Wang, H., Zhang, C., Wang, J., Guo, Y., & Liu, Q. (2021). Projecting heat-related excess mortality under climate change scenarios in China. *Nature Communications*, 12(1), 1039. https://doi.org/10.1038/s41467-021-21305-1

Yin, Y., Grundstein, A., Mishra, D. R., Ramaswamy, L., Hashemi Tonekaboni, N., & Dowd, J. (2021). DTEx: A dynamic urban thermal exposure index based on human mobility patterns. *Environment International,* 155, 106573. https://doi.org/10.1016/J.ENVINT.2021.106573

Appendices

Appendix A. Cooling Center Layer Creation Process

A1: Links to the data used for creating cooling center point and polygon layers

- Ready LA County website: https://ready.lacounty.gov/heat/
- 2017 County Cooling Center List: http://publichealth.lacounty.gov/docs/COOLING%20CENTER%20LIST%20Aug22-2017.pdf
- LA County ArcGIS Online Hub: https://egis-lacounty.hub.arcgis.com/
    - Non-County Libraries: https://egis-lacounty.hub.arcgis.com/datasets/libraries-1/explore
    - Non-County Centers: https://egis-lacounty.hub.arcgis.com/datasets/lacounty::senior-services-1/about (Senior Service Centers) https://egis-lacounty.hub.arcgis.com/datasets/lacounty::community-services/about (Community Service Centers)
    - Non-County Parks: https://egis-lacounty.hub.arcgis.com/datasets/lacounty::dpr-parks-as-points-public-hosted-feb-2022/explore?location=34.056284%2C-118.297523%2C9.67
    - Shopping Centers: https://lacounty.maps.arcgis.com/home/item.html?id=c195a00e75c445bbaab432bab9ff485f
    - Pools: https://lacounty.maps.arcgis.com/home/item.html?id=d0c91126553d46abbd01335bf8a03221
    - Recreation Centers: https://lacounty.maps.arcgis.com/home/item.html?id=5e739447d0344ff080de3306f7f28965
- LA County Service Locator: https://locator.lacounty.gov/
- California Protected Areas Database (CPAD): https://data.cnra.ca.gov/dataset/california-protected-areas-database

A2: Methodology for generating polygon layer for cooling centers

1) General naming conventions for finalized point/polygon layer
    - formal_(agency level)_(type)_(point/polygon)_(total# of centers)
        - Example: formal county layers

        - formal_county_point_103
        - Formal_county_park_polygon_13
  - informal_(type)_(point/polygon)_(total# of centers)
    - Example:
      - Informal_pool_point_107
  - Note: feel free to use your own naming conventions for the intermediate layers – just want to standardize the final layers for management!

2) Save frequently!

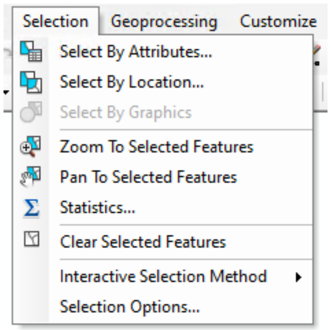
3) The below ArcMap steps are based on Xinyi's personal preference and logic. There are definitely alternatives that are easier or work better for you all, so feel free to edit, suggest, and add your workflows!

4) Overall logic:
   a) Import the point data layer and LARIAC layers (step 1)
   b) Intersect the LARIAC layer with point data to generate the building footprints for these points (step 2)
   c) Double check the footprints against google maps to ensure they match the centers (step 3)
   d) If there are points that do not intersect with any footprint (especially in a large number), different options:
      i) Use Google Maps as a reference, manually identify building footprint for each unmatched point (steps 4-7) **[accurate, but time-consuming & might work better for the centers with few unmatched points]**
      ii) Place a larger buffer around the point data to insect the surrounding buildings with this buffer, manually check through individual centers against maps, delete the nearby footprints that were intersected by 'accident' **[accurate, but also time-consuming] [but, /deletion/ might be easier than /selection and then combine to create a new layer/, especially for centers with a large number of unmatched points]**

Detailed Steps and Tools to Process Cooling Center Footprints

	ArcMap
1	Import the **cooling center point data layer** & **LARIAC layer** ● Note: can turn off the LARIAC layer so that the software will not load it (which takes really long)
2	**Use **"Selection by Location"**, instead of **"Intersect"** under "Geoprocessing"

tools, to get a sense of the # of centers matched with a footprint before exporting layers (“intersect” tool will directly generate the layer)

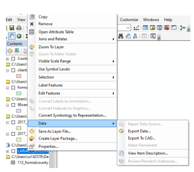


- Target layer: LARIAC layer
- Source layer: center point data layer
- Spatial selection methods: intersect the source layer feature
- Click “Apply”
  - Make sure to “clear selected features” before this step to prevent mixed-up selections
- Check the attribute table of the LARIAC layer to see if the number of feature selected in LARIAC layer matches with the total number of center points
  - Matches → go to step 3
  - Does not match → go to step 4
    - alternatively, add a **buffer** around the points and repeat this step to see if there are more intersections (especially if a huge number of your centers do not intersect with any footprint at all)

3

Matches :)

1) export the matched footprints as a new layer for manual checking



- Right-click the LARIAC layer (can remain turned-off) → Data → Export Data
- Export only **the SELECTED features** to a new layer and give meaningful names
- System dialog should pop up and ask if you want to import the layer

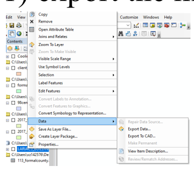
- After importing, manually check the point data location against the

building footprint to ensure that they are matched correctly
  - Use Google Map to match the building outline (the default layer is fine! But terrain layer & street views can be helpful in some cases)
  - LA County Service Locator is also a helpful tool to locate some of the facilities

- Tips when checking
  - keep the attribute table open
  - sort it in an order that you prefer (I use descending order for center address to keep track of my progress)
  - Start from the point at the top and go down the table in the sorted order
  - Select one point at a time, zoom to full extent and then zoom to the selected point (in blue) to check against footprint

4 **DOES NOT MATCH :(**

1) export the matched footprints as a new layer for manual checking



- Right-click on the LARIAC layer (can remain turned-off) → Data → Export Data
- Export only the **SELECTED** features to a new layer and give meaningful names
  - **footprint layer C**
- System dialog should pop up and ask if you want to import the layer

- After importing, manually check the point data location against the building footprint to ensure that they are matched correctly
  - Use Google Map to match the building outline (the default layer is fine! But terrain layer & street views can be helpful in some cases)
  - LA County Service Locator is also a helpful tool to locate some of the facilities

- Tips when checking:
  - keep the attribute table open
  - sort it in an order that you prefer (I use descending order for center address to keep track of my progress)
  - Start from the point at the top and go down the table in the sorted order
  - Select one point at a time, zoom to full extent and then zoom to the

selected point (in blue) to check against footprint

Note: if you see:

- More than one points intersect with one footprint
- One point intersects with more than one footprints

  → note down these points and footprints, as they will affect your results in step 6

- Then, go to step 5 for those without a matched footprint

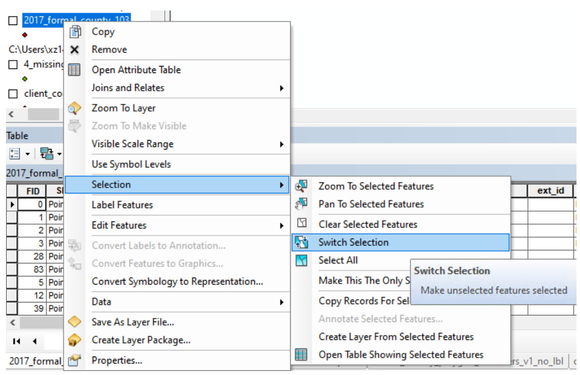
5

FOR POINTS WITHOUT INTERSECTED FOOTPRINTS

1) identify the points without a match (similar to step 2, but reverse source and target layers)

Use **"Selection by Location"**

- Target layer: center point data layer
- Source layer: LARIAC layer
- Spatial selection methods: intersect the source layer feature
- Click "Apply"
  - Make sure to "clear selected features" before this step to prevent mixed-up selections



- Right-click on the center point data layer → "Selection" → "Switch Selection"
- Check the attribute table before and after to see if the function is done correctly (I would suggest to keep the attribute table open and place it at the bottom of the interface to keep track of selections, if possible)
- Export these points as a new layer, name it accordingly, and import the exported layer
  - I will call this **point layer A** for reference in future steps

Note: if the number of selected point data in this reverse selection process does not match with the number of selected footprints in previous step, it might be due to

- More than one points intersect with one footprint
- One point intersects with more than one footprints

	• → you will find out when you complete step 4 • Go to step 6

6	**Create a layer of building footprints near the points in point layer A**
	
	Use the imported **point layer A** to selection by location again
	• Target layer: LARIAC layer
	• Source layer: **point layer A**
	• Spatial selection methods: intersect the source layer feature
	• **Click the checkbox next to "Apply a search distance" and input a distance**
	    ○ I did **200 meters**, which generate a reasonable layer that worked for all the formal county centers
	        ■ And many building footprints look very similar, so 200m buffer captures surrounding buildings, which serve as a reference for locating the exact center
	• Click "Apply"
	    ○ Make sure to "clear selected features" before this step to prevent mixed-up selections
	• Right-click the LARIAC layer (can remain turned-off) → Data → Export Data
	• Export only the **SELECTED** features to a new layer and give meaningful names (I will call this **footprint layer B**)
	• System dialog should pop up and ask if you want to import the layer
	• Import and go to step 7

7	**Manual checking for each point in point layer A against footprint layer B**
	
	• Manually check the point data location against the building footprint to look for the footprint of each point
	    ○ Use Google Map to match the building outline (the default layer is fine! But terrain layer & street views can be helpful in some cases)
	    ○ LA County Service Locator is also a helpful tool to locate some of the facilities (it will direct you to google map eventually)
	
	• Tips when checking
	    ○ keep the attribute table open
	    ○ sort it in an order that you prefer (I use descending order for center address to keep track of my progress)
	    ○ Start from the point at the top and go down the table in the sorted order
	    ○ Select one point at a time, zoom to full extent and then zoom to the

selected point (in blue) to check for corresponding footprint

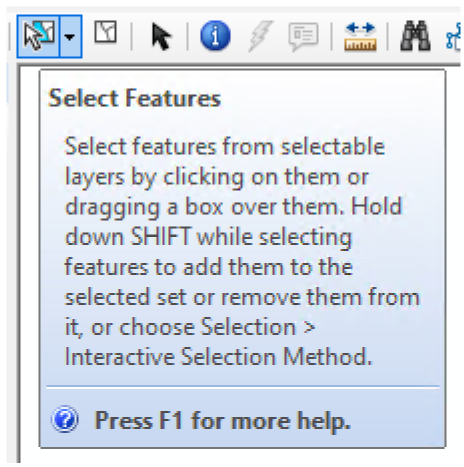
After locating the cooling centers, delete the nearby non-cooling center footprints. After checking through every point, merge this polygon layer with footprint layer C (step 4)

OR

(the method below is more tedious)

create a layer for these matched footprints (more tedious)

1) After zooming into the selected point and figuring out the matching footprint, use "select features" tool to select the footprint (make sure to clear all selections before this selection)

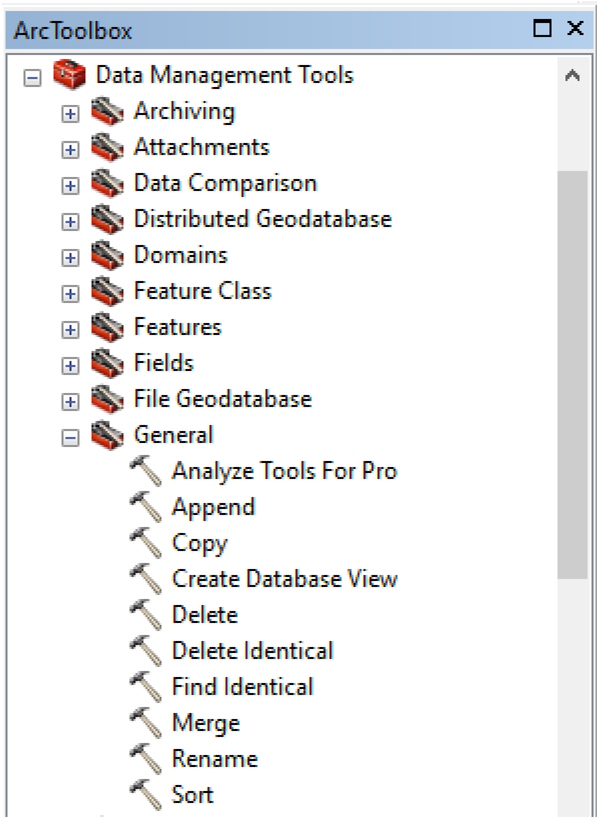


2) Check the attribute table, note down one unique attribute ('OBJECTID' or 'BLD_ID' (building ID) are good ones to use) → keep a list of the center and the matched building footprint
3) After identifying the footprint for all, use **"Selection by Attribute"** to select all these footprints and export data as a new layer - **footprint layer D**

Lastly,

Merge **footprint layer D** and **footprint layer C** **(step 4)**

- In ArcToolbox, open Data Management Tools → General → Merge



- Input: **footprint layer D** and **footprint layer C**

Appendix B. Complete Cooling Center List

B1: Cooling center summary statistics

	Formal County Cooling Centers			Formal Non-County Cooling Centers			Informal Cooling Centers			
Center Type	**Parks**	**Libraries**	**Centers**	**Parks**	**Libraries**	**Centers**	**Pools**	**Recreation Centers**	**Shopping Centers**	**SUM**
Number of centers	8	38	57	45	209	316	84	202	324	1283
Number of polygons	14	38	66	73	264	357	171	277	1208	2468
Total polygon area (sq. meter)	11,086	76,761	91,765	53,789	333,844	477,933	102,799	314,161	6,849,098	8,311,236
Total polygon area (sq. feet)	119,326	826,245	987,746	578,983	3,593,457	5,144,407	1,106,513	3,381,585	73,722,784	89,461,045
Total polygon area (acre)	2.74	18.97	22.68	13.29	82.49	118.10	25.40	77.63	1692.45	2053.75

B2: Link to Google Sheet with the complete cooling center list

https://tinyurl.com/2017LACoolingCenter

Appendix C. Full Weather Data of Study Period

C1: Temperature gradient for full study period

JULY 2017			AUGUST 2017		
DATE	TMAX_F	DEATHS	DATE	TMAX_F	DEATHS
7/1/2017	78.5	160	8/1/2017	82.9	183
7/2/2017	77.5	143	8/2/2017	95.7	188
7/3/2017	84.3	165	8/3/2017	94.3	181
7/4/2017	87.2	172	8/4/2017	92.1	174
7/5/2017	87.5	167	8/5/2017	87.6	167
7/6/2017	87.7	174	8/6/2017	85.5	155
7/7/2017	91.2	167	8/7/2017	84.7	187
7/8/2017	96.5	194	8/8/2017	84.5	151
7/9/2017	98.7	167	8/9/2017	87.7	162
7/10/2017	96.2	205	8/10/2017	85.9	161
7/11/2017	91.6	167	8/11/2017	87	151
7/12/2017	87.5	159	8/12/2017	86.7	156
7/13/2017	85.6	145	8/13/2017	85.9	147
7/14/2017	86	148	8/14/2017	85.8	169
7/15/2017	84.6	176	8/15/2017	79.8	142
7/16/2017	88.8	163	8/16/2017	77.1	166
7/17/2017	86.3	173	8/17/2017	80.4	147
7/18/2017	86.1	146	8/18/2017	81.9	164
7/19/2017	86.6	165	8/19/2017	81.9	141
7/20/2017	87.7	172	8/20/2017	82.3	167
7/21/2017	88.8	142	8/21/2017	81	148
7/22/2017	85.6	174	8/22/2017	81.5	152
7/23/2017	86.5	154	8/23/2017	84.2	170
7/24/2017	86.9	162	8/24/2017	80.2	180
7/25/2017	83.9	176	8/25/2017	80.5	141
7/26/2017	84.1	164	8/26/2017	82.5	151
7/27/2017	84.7	155	8/27/2017	90.4	162
7/28/2017	87	166	8/28/2017	87.7	161
7/29/2017	85.4	145	8/29/2017	93.4	177
7/30/2017	87.1	157	8/30/2017	97.2	193
7/31/2017	84.7	152	8/31/2017	95.9	173

C2: Selected study pairs temperature difference

Pair	Date_Baseline	Date_Hot	T_Difference
1	7/1/2017	7/8/2017	18
2	7/2/2017	7/9/2017	21.2
3	7/26/2017	8/2/2017	11.6
4	7/27/2017	8/3/2017	9.6
5	8/23/2017	8/30/2017	13
6	8/24/2017	8/31/2017	15.7

Appendix D. Python Script for Mobility Data Processing

Practicum LAC Mobility Data Processing 2021-2022

May 19, 2022

1 Processing

[ ]:
```
!pip install geopandas
import pandas as pd
import geopandas as gpd
import numpy as np
from datetime import datetime
from shapely.geometry import Point, shape
from tqdm import tqdm
import rtree

##load in mobile data by day
df = pd.read_csv("df.csv")

## MOBILE DATA QUERYING
#remove ID rows with horizontal accuracy > 25m
#take a distribution to find a cutoff value, maybe too many NA and cant take␣
↪out, might need to rely on large numbers
df = df[df["horizontal_accuracy"] <= 25]

#remove id rows with speed > 3 m/s or NA; 3m/s, encapture walking distance
df = df[(df["speed"] <= 3) | (df['speed'] == 'NA')]

##filter for hourly time

for time in [(12:00:00, 12:59:59), (13:00:00, 13:59:59), (14:00:00, 14:59:59),␣
↪(15:00:00, 15:59:59)]:
  date = '2017-07-01' #change for individual study days
  df['newtime'] = pd.to_datetime(df['LocalTime'])
  df_queried = df.loc[(df['newtime'] >= date + time[0]) & (df['newtime'] <=␣
↪date + time[1])]

#ADD COORDINATE COLUMN
df_queried['coordinates'] = list(zip(df_queried['longitude'],␣
↪df_queried['latitude']))
```

2 Import center shapefiles

[ ]:
```
#Key:
#I = informal
#NC = non-county formal
#FC = county formal

#store names of center in a list for calling
#ensure downloaded files are in same depository as script and each center is␣
↪named the same as name in
center_list = ['FC_center', 'FC_library', 'FC_park',
               'NC_center', 'NC_library', 'NC_park',
               'I_pool', 'I_rec', 'I_shop']

transformed_shp = [] #define empty list to store transformed shp
#read in files from local database/repository
for type in center_list: #type is a string name
  type + 'shp' = gpd.read_file('/file_path/' + type + '.shp')
  type + 'tran' = type+'shp'.to_crs(epsg=4326) #project shp into WGS84␣
↪reference ellipsoid
  transformed_shp.append(type + 'tran')

geometry_files = []
#define and draw the center building polygons based on the geometry column
for file in transformed_shp:
   file = file['geometry']
   geometry_files.append(file)

locations = {
    "formal_center": FCcenter_tran['geometry'],
    "formal_library": FClibrary_tran['geometry'],
    "formal_park": FCpark_tran['geometry'],
    "pool": Ipool_tran['geometry'],
    "shops": Ishops_tran['geometry'],
    "recreation": Irec_tran['geometry'],
    "non_parks": NCparks_tran['geometry'],
    "non_libraries": NClibraries_tran['geometry'],
    "community": NCcommu_tran['geometry']
}
```

3 1.1 Duration

[ ]:
```
#install following packages
!pip install geopandas
import pandas as pd
import numpy as np
```

```
        return np.nan

    def apply_finder(self, csv):
      # csv['coordinates'] = list(zip(csv["longitude"], csv['latitude']))

      csv[self.location_name] = csv['geometry'].apply(self.finder)
      return csv

# input, a list of csvs, a list of location files
# output, the same list of csvs but with a new column for each location file
```

5 Q2 Demographics

[ ]:
```
for location_name, location in tqdm(locations.items()):
  finder_object = Find_location(location, location_name)
  mobile_id_gdf2 = finder_object.apply_finder(mobile_id_gdf)
```

[ ]:
```
# sovi_shpfile > already in tracts

sovi_shpfile= gpd.read_file("/content/drive/Shareddrives/Practicum: LA County␣
 ↪Heatwaves/Data/SOVI/LA_CVA_Social_Sensitivity_Index_export/
 ↪LA_CVA_Social_Sensitivity_Index_0.shp")
sovi_thirds = sovi_shpfile.to_crs(epsg=4326)
```

[ ]:
```
# date
# mobile_id_clean= pd.read_csv("/content/drive/Shareddrives/Practicum: LA␣
 ↪County Heatwaves/Data/Code/Q2: Daily center locations/clean/clean_august30.
 ↪csv")
mobile_night = csv2.loc[(csv2['newtime'] >= '2017-07-09 01:00:00') &␣
 ↪(csv2['newtime'] <= '2017-07-09 04:59:59')]
mobile_day = mobile_id_clean.drop_duplicates('advertiser_id')

ids_at_night = mobile_night.loc[mobile_night['advertiser_id'].
 ↪isin(mobile_day['advertiser_id'].unique())]
ids_at_night = gpd.GeoDataFrame(ids_at_night, geometry=gpd.
 ↪points_from_xy(ids_at_night.longitude, ids_at_night.latitude))
ids_at_night = ids_at_night.set_crs(epsg=4326)
ids_at_night = ids_at_night.drop_duplicates(subset = ['advertiser_id'])
ids_in_sovi = sovi_thirds.sjoin(ids_at_night)
```

[ ]:
```
(cold_com.groupby(['latitude', 'longitude'])['SoVI_Third'].mean())
```

[ ]:
```

```

```
#Load in hourly occupancy tables
file1 = pd.read_csv("/file_path/8-31 12pm Table.csv")
file2 = pd.read_csv("/file_path/8-31 1pm Table.csv")
file3 = pd.read_csv("/file_path/8-31 2pm Table.csv")
file4 = pd.read_csv("/file_path/8-31 3pm Table.csv")

#Remove N/A points (ones not found in cooling centers)
day_0 = file1.dropna(subset = ['location'])
day_1 = file2.dropna(subset = ['location'])
day_2 = file3.dropna(subset = ['location'])
day_3 = file4.dropna(subset = ['location'])

#Bind by day
all = pd.concat([filter_8_31_0,filter_8_31_1,filter_8_31_2,filter_8_31_3])
all

#Group by location and view table of the unique pings
table = all.groupby("location")["advertiser_id"].nunique()
table
```

4 Example

```
[ ]: j1 = pd.read_csv("/file_path/")
j1 = j1[j1["horizontal_accuracy"] <= 25]
j1['newtime'] = pd.to_datetime(j1['LocalTime'])
j1_2 = j1.loc[(j1['newtime'] >= '2017-07-01 1:00:00') & (j1['newtime'] <=␣
↪'2017-07-01 4:59:59')]

class Find_location:
  def __init__(self, location, location_name):
    self.location = location
    self.location_name = location_name

  def finder(self,geom):
    points = self.location.contains(geom)
    # self.location.distance(geom) < cutoff aka a buffer ust do to see if we␣
↪should do it to capture more
    valid_set = self.location[points]

    if sum(points)>0:
      return valid_set
      # print(type(MultiPolygon(valid_set.to_list())), MultiPolygon(valid_set.
↪to_list()))
      # return MultiPolygon(valid_set.to_list())
    else:
```

Appendix E. Detailed Methodology for Resting Location to Cooling Center

E1: ArcGIS workflow to calculate resting location of users to cooling center used during the day

Methodology Steps:

1. Aggregate the CSV files for hot and baseline days containing

FOR THE CSVs:

- Aggregate the hot days and baseline/cold days
- Pull out the rows for each center type and put into one csv file
- → END RESULTS: 18 csv files in total -> e.g. hot_county_park, baseline_county_park, etc.
- THEN extract the index from all 18 files → step 1 below

1. **Extract the OBJECT_ID from the excel sheet (SOVI_ID file)**

- =LEFT (cell, # grab)
  - EX. =LEFT(M2, 3)
- cell= original string
- # grab = characters from left to grab

NOTES: USE THE REPROJECTED SHAPEFILE FOR CENTER POLYGON LAYERS! → FID starting from 0, which matches with the index on python

2. **Merge the polygon layer with the excel table to get the cooling center information**
   a. **!!! USE POLYGON LAYERS IN THIS FOLDER: Projected Polygon Layer shapefile**
      i. FID starting from 0 → matched with the python index
      ii. ALSO Reprojected to WGS 1984 UTM Zone 11N to make sure the linear unit is in meter
   b. Download as csv file into arc (**use the locations data files in this folder: Sovi and IDs by_centers)**
   c. Use table to table to convert the csv file to gdb tables → or else will get the NO OID ERROR when joining fields
      i. Table To Table (Conversion)—ArcGIS Pro
      ii. Table To Table (Conversion)—ArcMap | Documentation
   d. Join the cooling center polygon layer attributes to the table: Join Field (Data Management)—ArcGIS Pro
      i. Input table: the newly generated gdb table
      ii. Input Join field: extracted index from the excel
      iii. Join Table: Polygon layer
      iv. Join Table field: FID or OBJECT_ID, depending on specific layer

(=========== SKIP STEP 3 ===========)

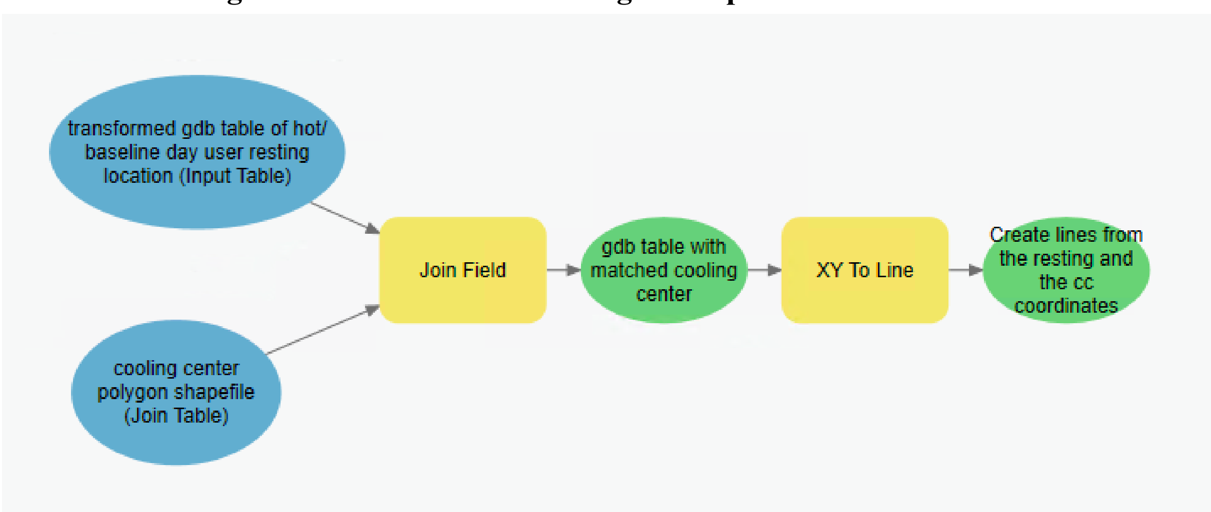
3. **Match the cooling center from polygon layer to the point layer → done with the cooling center names or any other common field**
    a. Join the cooling center point layer information to the table: [Join Field (Data Management)—ArcGIS Pro]
        i. Input Table: the newly generated gdb table
        ii. Input Join field: Name (joined from polygon layer in the last step)
        iii. Join Table: Point layer
        iv. Join Table field: Name

NOTES: ALL polygon layers have the point layer latitude longitude information → SKIP

(=========== SKIP STEP 3 ===========)

4. **Create lines from the resting coordinates and the cc coordinates**
    a. [XY To Line (Data Management)—ArcGIS Pro | Documentation]
    b. Input Table: the newly generated gdb table
    c. Start X: resting location longitude
    d. Start Y: resting location latitude
    e. Ending X: cooling center longitude
    f. Ending Y: Cooling center latitude
    g. Some visuals of how the lines look like: Some visuals for rest to cc!!

Automation using ArcGIS Pro Model Building for step 2d to 4

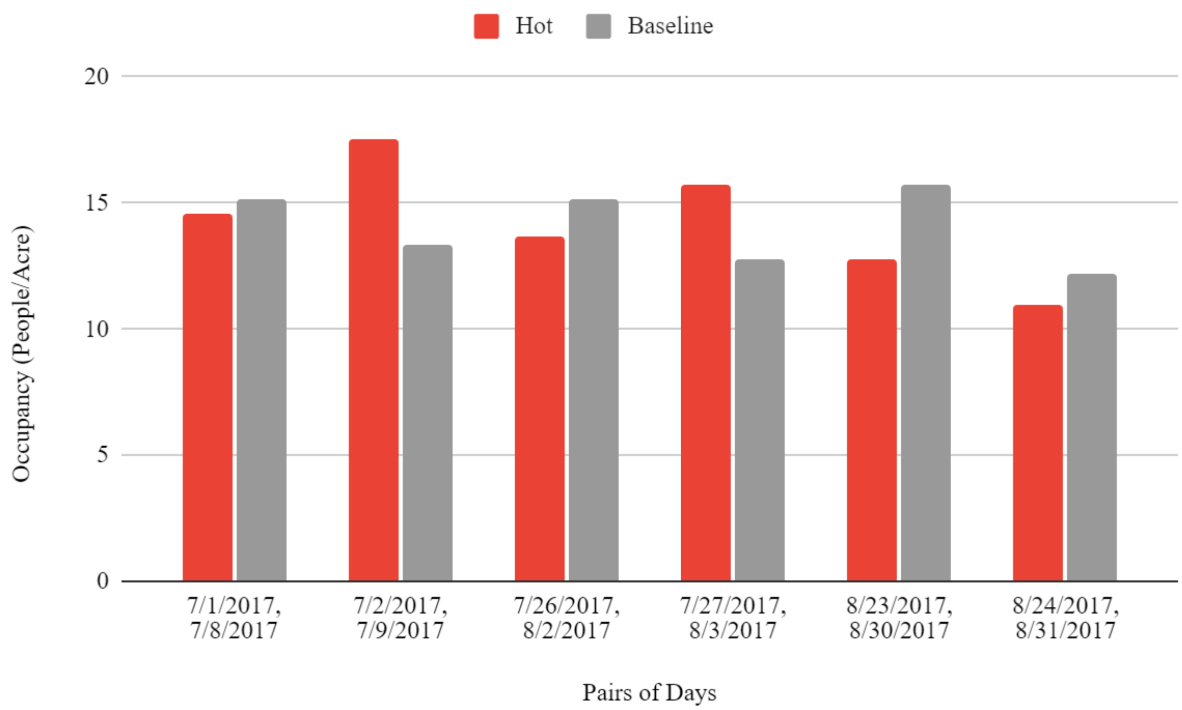


5. **Calculate the line distances**
    a. Create new field: ‘Distance_m’, DOUBLE, NUMERIC

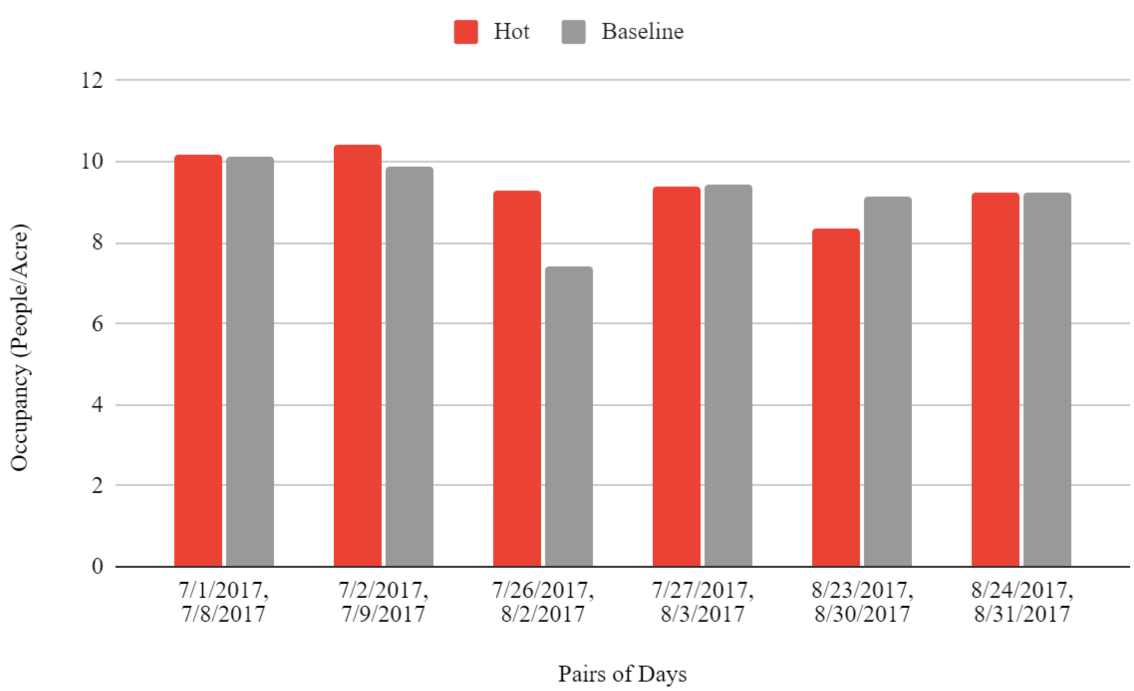
b. Calculate Geometry for the field ‘Distance_m’, choose length(geodesic), unit: meters, projection: WGS 1984 UTM 11N
c. Export to csv files
d. Also uploaded the ArcGIS project folder with the geodatabase of all these files

Appendix F. Occupation Analysis Additional Figures

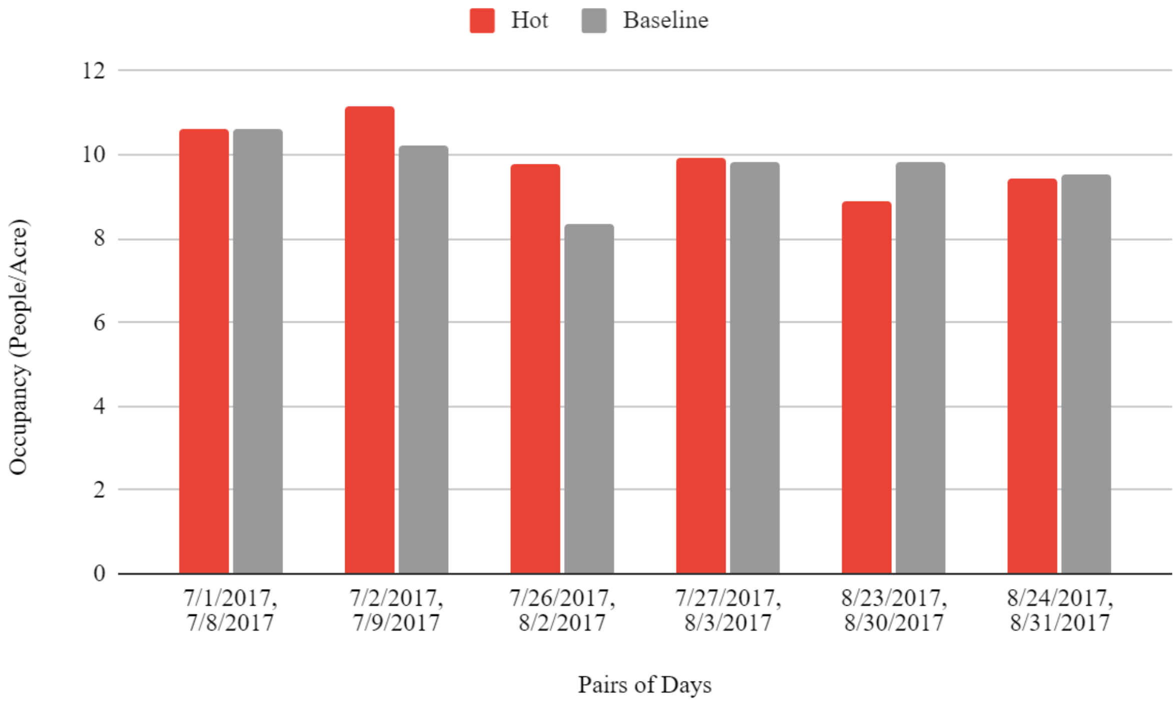
F1: Formal non-county cooling center occupancy of paired hot and baseline days



F2: Informal cooling center occupancy of paired hot and baseline days



F3: Combined cooling center occupancy of paired hot and baseline days



Appendix G. R Script for Statistical Analysis of Hot and Baseline Use

```
##IMPORT DATA (4 csv's containing H/C pairs)

#formal county cooling centers
formal_county_pairedt <-
read_csv("C:/Users/Desktop/formal_county_pairedt.csv")

#formal non-county cooling centers
formal_nocounty_pairedt <-
read_csv("C:/Users/Desktop/formal_nocounty_pairedt.csv")

#informal cooling centers
informal_pairedt <-
read_csv("C:/Users/Desktop/informal_pairedt.csv")

#all cooling center types
total_pairedt <- read_csv("C:/Users/Desktop/total_pairedt.csv")

##RUN PAIRED T-TESTS

#formal county
t.test(formal_county_pairedt$hot_form_c,
formal_county_pairedt$cold_form_c
    , mu = 0, alt="two.sided",paired=T, conf.level=0.99)


#formal non-county
t.test(formal_nocounty_pairedt$hot_form_nc,
formal_nocounty_pairedt$cold_form_nc
       , mu = 0, alt="two.sided",paired=T, conf.level=0.99)

#informal
t.test(informal_pairedt$hot_form_nc,
informal_pairedt$cold_form_nc
       , mu = 0, alt="two.sided",paired=T, conf.level=0.99)

#all types
t.test(total_pairedt$hot_form_nc, total_pairedt$cold_form_nc
       , mu = 0, alt="two.sided",paired=T, conf.level=0.99)
```

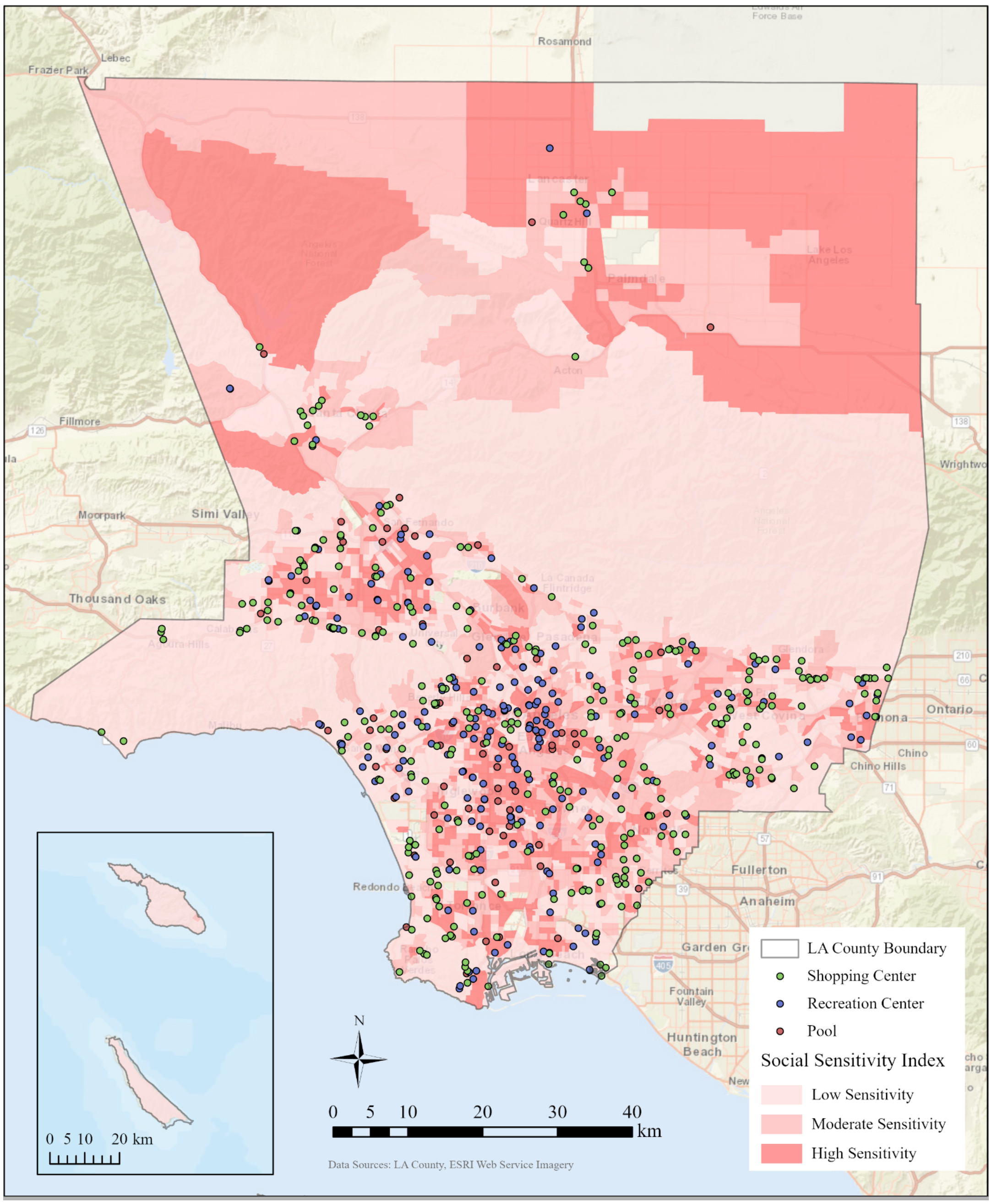
Appendix H. Vulnerability Analysis Additional Figures

H1: Vulnerability index variables initially considered (if we were to make it ourselves) VS LA County SSI variables

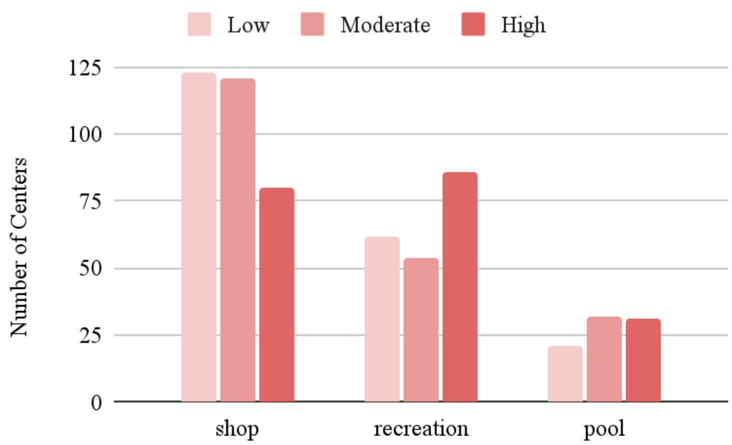
Student 2017 ACS		Los Angeles County	
EDUCATION	DP02_0061PE Percentage of Adults 25+ with a high school diploma	AGE	Children, older adults, older adults living alone
EDUCATION	DP02_0064PE Percentage of Adults 25+ with a bachelor's degree	COMMUNITY & LANGUAGE	Foreign-born, female, female household, library access, voter turnout rate, limited English proficiency
INCOME & WEALTH	DP03_0063E income and benefits (in 2017 inflation-adjusted dollars)	OCCUPATION	Outdoor worker (including agriculture, fishing, mining, extractive or construction occupations), unemployment
INCOME & WEALTH	DP03_0128PE Percentage of families and people whose income in the past 12 months is below the poverty level	EDUCATION	No high school diploma
AGE	DP05_0014E Total population - 60 to 64 years	HEALTH	Disability, asthma, cardiovascular disease, no health insurance
AGE	DP05_0016E Total population - 75 to 84 years	HOUSING	Living in group quarters, mobile homes, cost-burdened, renters
TRANSPORTATIO N	B08201 - housing units with car	INCOME & WEALTH	Median income, poverty
	Racial demographics, pre-existing conditions, the people who	RACE & ETHNICITY	Black, Asian, Hispanic/Latinx, Indigeous
		ACCESS TO	No internet

	commute to work via car	INFORMATION	
		TRANSPORTATIO N	Households without vehicles, transit access

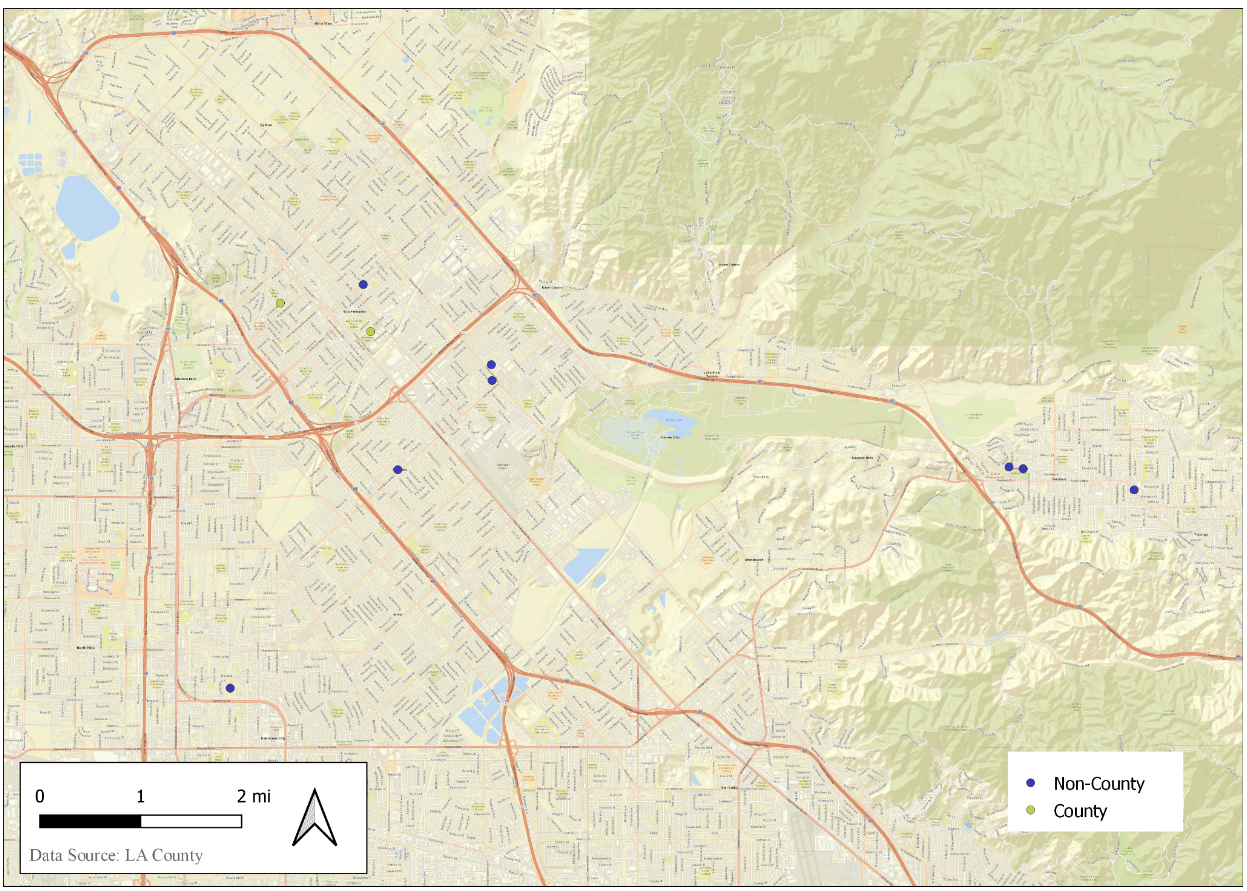
H2. Informal cooling centers and SSI tracts in 2017



H3: Informal cooling center counts by SSI Thirds



H4: Map of formal cooling centers comprising the Pacoima area of the San Fernando Valley



Appendix I. Interview Script and Responses

OUTREACH SCRIPT:
Hi my name is [student name] and I am reaching out on behalf of a UCLA research team and the LA County Dept of Public Health. We reached out to you as this [location] is listed as a public cooling center for LA during heatwaves. Would you have some time either now or at another scheduled hour to discuss some aspects of the facility and how it operates as a cooling center?

PREPARED INTERVIEW QUESTIONS AND RESPONSE NOTES:

<table>
<tr><th colspan="2">What do people generally do when they are at your facility as a cooling center?</th></tr>
<tr><td>Response 1:
Nobody except maybe once or twice people have called to ask if the library is a cooling center
Have a lot of younger homeless people going into use the library, not really any elderly people
Nobody is coming in for a cooling center - when people go in, they aren't going in saying they are thinking to go to cool off, but that’s what they are doing just to go in</td><td>Response 2:
Most folks are there to read, use computers (quite a bit), sit inside to use laptops or phones
People are representative of the community demographics (racially, socioeconomically)
All library branches have people counters, but official usage is not used</td></tr>
<tr><th colspan="2">Do you have an official process for opening as a cooling facility when it is hot outside?</th></tr>
<tr><td>Response 1:
N/A</td><td>Response 2:
No official process other than letting people know on social media. No signage, no changes in operation.</td></tr>
<tr><th colspan="2">Do you communicate with the general public about the facility being open as a cooling center, like signage outside?</th></tr>
<tr><td>Response 1:
N/A</td><td>Response 2:
Administration (council members) tells the operators when to operate as cooling center, and facility complies</td></tr>
</table>

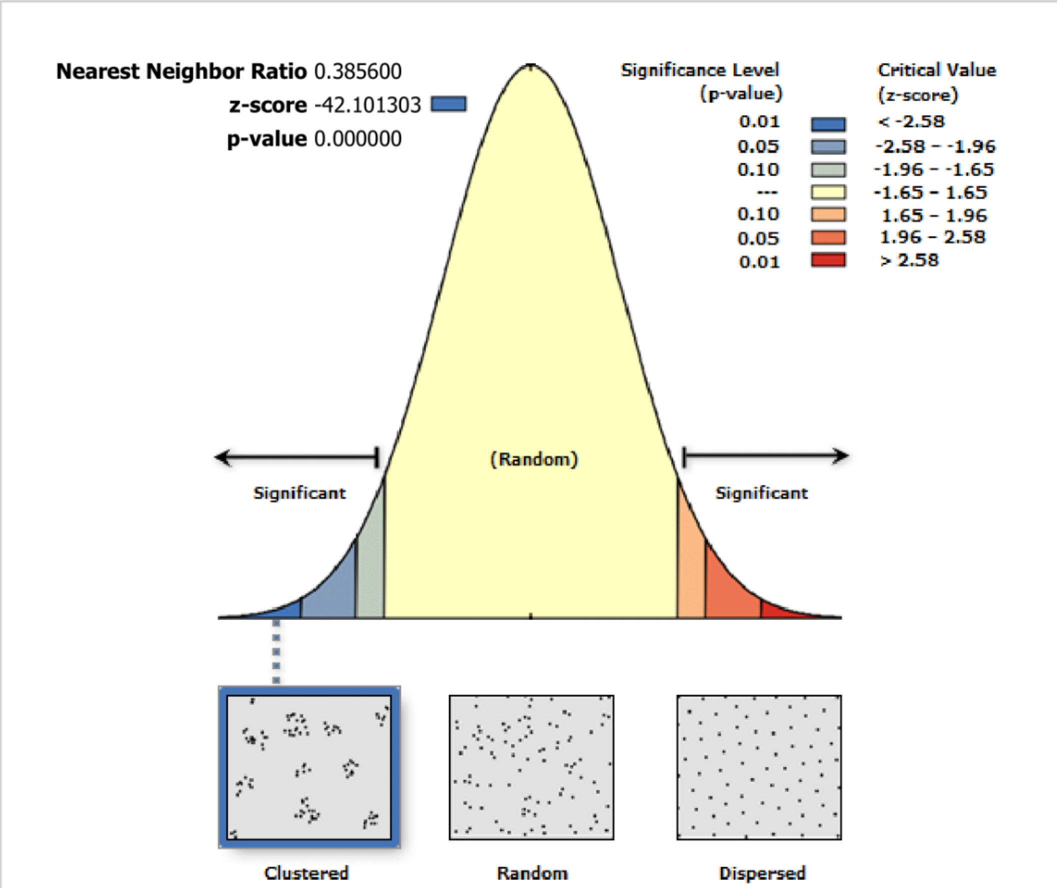
	● Advertisements sent out on social media
Do you think it'd be easiest to get to the center by car or by public transportation?	
Response 1: ● Bus stops close by, different strata - people with houses and cars, they don't really need as cooling, but people who need public transportation - recommends contacting senior centers nearby to see how they transport seniors	Response 2: ● N/A
What is the procedure like for activating the center? Who provides the directive to open?	
Response 1: ● Not that hot right now so not a cooling center now; around 110 degrees, when it gets super hot, la county + la city makes them cooling centers ● Believes that it is put on website to let people know; city will also buy water when its hot ● Major problem is digital divide - all info for people who need to be reached is generally distributed via internet, but this misses elderly + homeless who tend to not be online / internet is not accessible	Response 2: ● N/A
What do you see as the biggest challenge to operating as a cooling center?	
Response 1: ● N/A	Response 2: ● Getting the word out is the biggest challenge, non-regular patrons realizing that they can use this facility as a cooling center

<table>
<tr><td></td><td>However, people who frequent the facility know that it acts as a cooling center</td></tr>
<tr><td colspan="2">How do you think cooling centers/heat resilience efforts can be improved to better serve the community?</td></tr>
<tr><td>Response 1:
N/A</td><td>Response 2:
Getting more trees in communities, shade closer to home. Tree shade varies around the area
More cooling center facilities
Capacity of this center is 68 people at one time. Have reached the number in the past
Transportation is an issue, even though there is a bus stop in front of the building. Observationally speaking, is a very popular way for patrons to get to the facility</td></tr>
</table>

Appendix J. Transportation Analysis Additional Figures

J1: Nearest neighbor gaussian curves for all cooling centers

Average Nearest Neighbor Summary



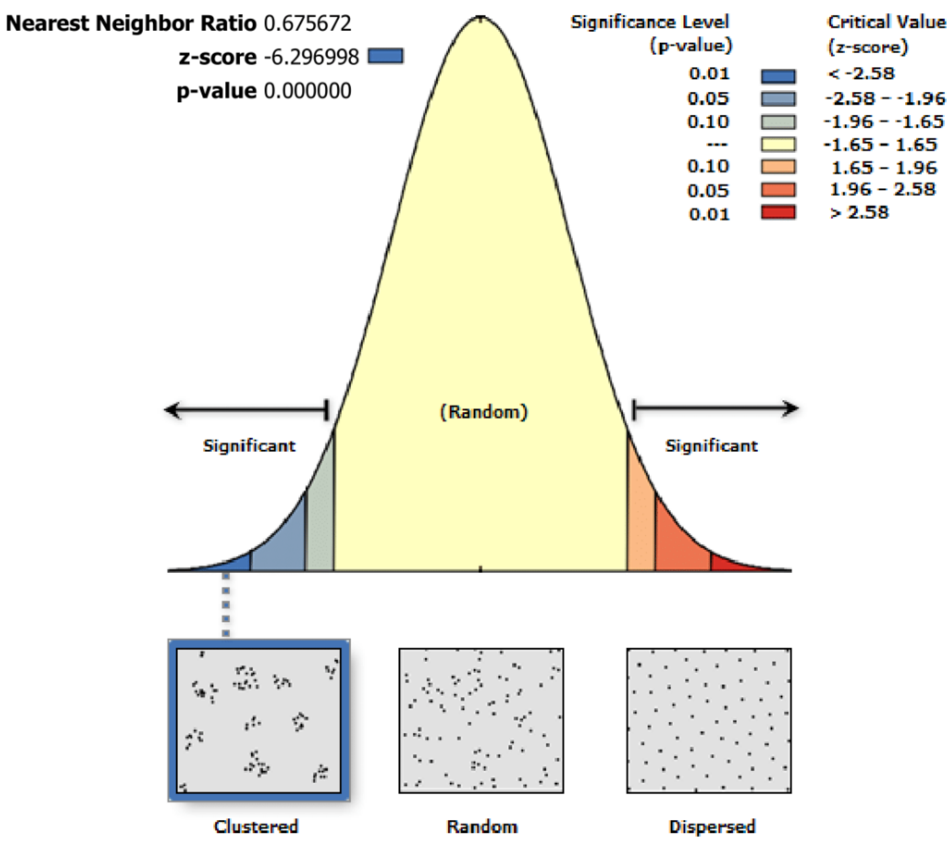
Given the z-score of -42.101303, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Average Nearest Neighbor Summary

Observed Mean Distance	628.2383 Meters
Expected Mean Distance	1629.2494 Meters
Nearest Neighbor Ratio	0.385600
z-score	-42.101303
p-value	0.000000

J2: Nearest neighbor gaussian curves for all formal county cooling centers

Average Nearest Neighbor Summary



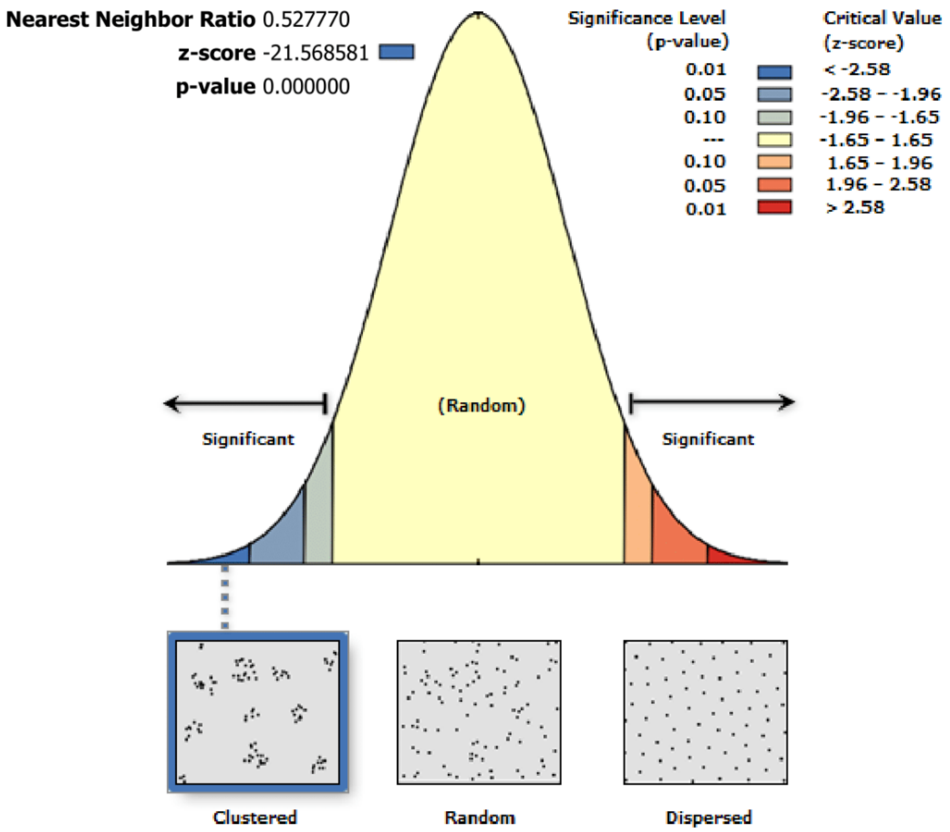
Given the z-score of -6.296998, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Average Nearest Neighbor Summary

Observed Mean Distance	3674.1243 Meters
Expected Mean Distance	5437.7315 Meters
Nearest Neighbor Ratio	0.675672
z-score	-6.296998
p-value	0.000000

J3: Nearest neighbor gaussian curves for all formal non-county cooling centers

Average Nearest Neighbor Summary



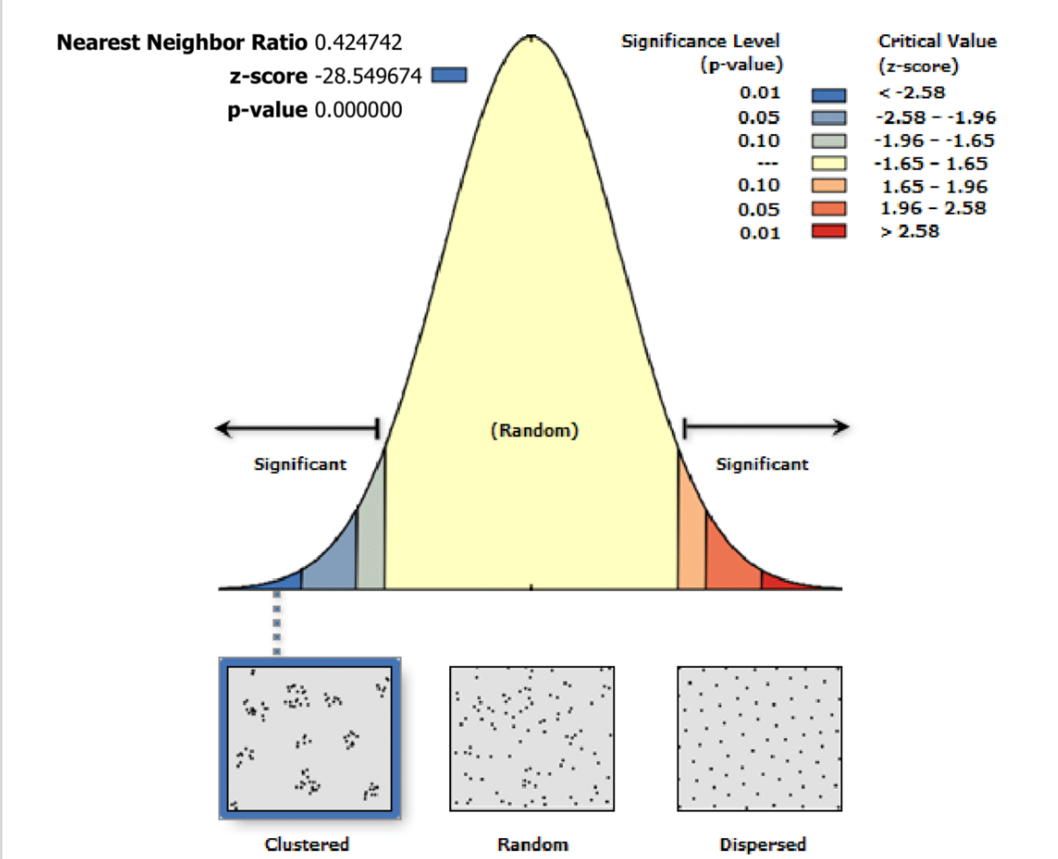
Given the z-score of -21.568581, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Average Nearest Neighbor Summary

Observed Mean Distance	1064.1474 Meters
Expected Mean Distance	2016.3077 Meters
Nearest Neighbor Ratio	0.527770
z-score	-21.568581
p-value	0.000000

J4: Nearest neighbor gaussian curves for all formal cooling centers (county & non-county)

Average Nearest Neighbor Summary



Given the z-score of -28.549674, there is a less than 1% likelihood that this clustered pattern could be the result of random chance.

Average Nearest Neighbor Summary

Observed Mean Distance	953.1338 Meters
Expected Mean Distance	2244.0305 Meters
Nearest Neighbor Ratio	0.424742
z-score	-28.549674
p-value	0.000000

J5: Map of 2017 Public Transit Stops in LA County